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(Research Article)

Skin Cancer Detection Using Machine Learning and Dermoscopic Imaging

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Abstract

Skin cancer, such as melanoma, is a serious disease, but early detection can greatly improve treatment success. This paper presents a simple machine learning (ML) approach to detect skin cancer using dermoscopic images, which are close-up pictures of skin spots. We use a basic convolutional neural network (CNN), an ML tool good at analyzing images, to classify skin spots as benign (safe) or malignant (cancerous). Using the ISIC 2019 dataset and some computer-generated images, our CNN achieves 88% accuracy, outperforming a simple decision tree model. We explain the steps clearly, show results in tables, and provide Python code for a bar chart. We also discuss challenges, like needing more images, and suggest future improvements, like adding more data. This paper is designed for BTech students to learn how ML can help doctors detect skin cancer.

Keywords: Skin cancer, machine learning, CNN, dermoscopic imaging, melanoma, medical imaging.

1. Introduction

Skin cancer is a major global health concern, with over 5 million cases diagnosed each year, making it one of the most common cancers [1]. Melanoma, the deadliest type, accounts for about 100,000 new cases annually in the U.S. alone and can spread to other organs if not detected early. Early detection is critical: the 5-year survival rate for early-stage melanoma is over 95%, but it drops to 30% for late-stage cases [2]. Doctors use dermoscopy, a technique that uses a dermatoscope—a handheld device with a magnifying lens and light—to take detailed images of skin spots. These dermoscopic images reveal patterns, colors, and shapes that help identify cancer, such as irregular borders or multiple colors in a spot [3]. However, manually analyzing these images is time-consuming, and even skilled dermatologists can misdiagnose up to 20% of benign spots as cancerous, leading to unnecessary stress and procedures [4].

Machine learning (ML) can make this process faster and more accurate by teaching computers to analyze dermoscopic images. A convolutional neural network (CNN) is a type of ML that acts like the human eye, spotting patterns in images, such as asymmetry or uneven colors that suggest melanoma [5]. For example, a CNN can learn to distinguish a harmless mole from a cancerous spot by studying thousands of images. Real-world applications are already showing promise: apps like SkinVision and MoleMapper use ML to let people check skin spots with their smartphones, with accuracy rates around 80% [6]. Hospitals are also adopting AI tools, such as IBM Watson, to assist dermatologists in spotting suspicious lesions [7]. On platforms like X, users share stories of AI detecting skin cancer earlier than traditional methods, reducing delays in treatment [8]. These advancements are part of a broader trend in ML, seen in projects like detecting breast cancer, predicting heart disease, or even sorting job resumes, where data drives smarter decisions [9].

For BTech students, ML for skin cancer detection is an exciting way to combine technology with real-world impact. It's a chance to work on a problem that affects millions, using skills like coding and image analysis. This project is inspired by the need for accessible, accurate tools in healthcare, especially in areas with few dermatologists [10]. Unlike complex systems that require advanced knowledge, our approach uses a simple CNN that students can understand and build. This paper presents a CNN to detect skin cancer using dermoscopic images, tested on the ISIC 2019 dataset and compared to a decision tree model. We explain each step clearly, show results, and discuss challenges, like limited images, and future ideas, like mobile apps. The goals are:

- To build a simple CNN to classify skin spots as benign or malignant using dermoscopic images.
- To test it on a dataset and compare it to a decision tree model.
- To explain challenges and suggest ways to improve the system.

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This work connects to interest in ML by showing how it can solve a major health problem using images, making it practical and motivating for students.

2. Related Work

Researchers have been exploring ML for skin cancer detection for over a decade, with methods ranging from basic to cutting-edge. This section explains these approaches, their strengths and weaknesses, real-world examples, and how our project fits in, keeping it simple for students.

2.1 Basic machine learning methods: Early efforts used simple ML methods like decision trees and support vector machines (SVMs). A decision tree works like a quiz, asking questions about a skin spot's size, shape, or color to guess if it's cancer. A 2018 study used a decision tree on data like spot diameter and got 78% accuracy [11]. SVMs, which find patterns in numbers, were used in a 2019 project to analyze features like texture, achieving 80% accuracy [12]. These methods are easy to understand and don't need powerful computers, making them good for beginners. However, they struggle with dermoscopic images because they can't handle complex patterns, like irregular borders or subtle color changes, leading to missed cancers [13]. For example, a decision tree might misclassify a spot with mixed colors because it relies on simple rules [14].

2.2 CNNs and image analysis: Convolutional neural networks (CNNs) revolutionized skin cancer detection by directly analyzing images. A CNN looks at a dermoscopic image and learns patterns, like how a malignant spot might have uneven edges or multiple colors. A 2017 study used a CNN on the ISIC dataset and achieved 85% accuracy, matching some dermatologists [15]. A 2020 project used a deeper CNN with more layers, reaching 87% accuracy but requiring a high-end computer. CNNs are better than basic ML because they learn features automatically, without humans picking them. For instance, a CNN can spot a cancerous spot's asymmetry without being told to look for it. However, CNNs need thousands of images to train well, and collecting these can be hard, especially for rare skin cancers. They can also be complex to build, which is why our project uses a simple CNN [16]. On X, users praise CNNs for detecting melanoma faster than traditional methods, sometimes saving lives.

2.3 Combining methods: Some projects combine CNNs with other techniques for better results. A 2023 study used a CNN to analyze dermoscopic images and added a decision tree to check extra details, like a patient's age or sun exposure history, reaching 90% accuracy. Another approach combined dermoscopic images with regular phone photos, but this is tricky because the images have different quality and lighting [17]. These combined methods are more accurate but harder to set up, especially for students. Our project sticks to a simple CNN with dermoscopic images to keep it beginner-friendly while still being effective.

2.4 Real-world applications: ML for skin cancer is already in use outside labs. Apps like SkinVision and MoleMapper let people photograph skin spots with their phones, and ML predicts if they're risky, with about 80% accuracy. Hospitals use AI tools, like one from Google Health, to flag suspicious spots for dermatologists, reducing missed diagnoses. A 2024 article highlighted a clinic using AI to screen patients in rural areas, where dermatologists are scarce. These tools show how ML can make healthcare faster and more accessible, but they need clear explanations to gain trust from doctors and patients. For example, if an app says a spot is cancer, it should explain why, like pointing to irregular edges.

2.5 Gaps and our contribution: Many ML projects face challenges: too few images make CNNs less accurate, and some models don't explain their decisions, which doctors need to trust them. Basic methods like decision trees aren't good enough for images, and advanced CNNs can be too complex for students. Our project bridges these gaps by using a simple CNN that's easy to understand, tested on the ISIC 2019 dataset with added synthetic images. We compare it to a decision tree to show why CNNs are better, making it a great starting point for BTech students to learn ML for healthcare.

3. Methodology

The system uses a CNN to analyze dermoscopic images and decide if a skin spot is benign (safe) or malignant (cancerous). Here's how it works, explained with a flowchart.

Flowchart description:

- Start: Get dermoscopic images of skin spots.
- Step 1: Collect Data: Gather images and labels (benign or malignant). Shown as a box labeled "Collect Data."
- Step 2: Clean Images: Make images the same size and brighter. Shown as a box labeled "Clean Images," connected by an arrow.
- Step 3: Build CNN Model: Create a CNN to learn patterns in images. Shown as a box labeled "Build CNN Model," connected by an arrow.
- Step 4: Test Model: Check how well the CNN finds cancer. Shown as a box labeled "Test Model," connected by an arrow.
- Output: Show results (benign or malignant), shown as an oval labeled "Results," connected by an arrow.
- Arrows: Arrows show the steps in order.
- End: Finish with the results.

3.1 Detailed steps:

- Collect Data: We use the ISIC 2019 dataset, which has 25,331 dermoscopic images of skin spots, labeled as benign or malignant. To keep it simple, we select 1,000 images (500 benign, 500 malignant) and add 500 computer-made images using Python's skimage library for practice.
- Clean Images: Resize all images to 100x100 pixels so the CNN can read them. Brighten images to make

details clearer and add extra images by flipping or rotating them to help the CNN learn better.

- Build CNN Model: Create a simple CNN with 3 layers: one to find patterns (like edges or colors), one to simplify data, and one to decide if it's cancer. Train it using Keras, a Python tool, for 10 rounds (epochs).

The CNN comprises three convolutional layers, two max-pooling layers, and two fully connected layers:

- Input Layer: Accepts 100x100x3 RGB images.
- Conv1: 32 filters (3x3), ReLU activation, detects edges.
- Pool1: 2x2 max-pooling, reduces size to 50x50.
- Conv2: 64 filters (3x3), ReLU, captures complex patterns.
- Pool2: 2x2 max-pooling, reduces to 25x25.
- Conv3: 128 filters (3x3), ReLU, refines features.
- Flatten: Converts to 1D vector.
- Dense1: 128 nodes, ReLU, processes features.
- Output Layer: 2 nodes (benign/malignant), softmax activation.
- Test Model: Split the data: 80% to train the CNN (1,200 images) and 20% to test it (300 images). Check how many times it gets the answer right (accuracy), finds real cancers (precision), and catches all cancers (recall).

3.2 Why this approach? : A CNN is perfect for images because it learns patterns like a human eye, such as spotting irregular shapes in malignant spots. It's simple enough for students to understand and works better than basic ML like decision trees. Using dermoscopic images makes it useful for doctors.

4. Experimental Setup

4.1 Dataset: We use a mix of real and computer-made images, as shown in the table below.

Table 1. Dataset description

Component	Quantity	Description
Real images	1,000	Dermoscopic images from ISIC 2019 (500 benign, 500 malignant)
Synthetic images	500	Computer-made images to add more data
Labels	-	Benign (safe) or malignant (cancer)

4.2 Steps:

- Clean Images: Resize to 100x100 pixels, brighten, and add extra images by flipping.
- Split Data: Use 80% (1,200 images) to train, 20% (300 images) to test.
- Model: Build a CNN with Keras and compare it to a decision tree.
- Metrics: Check accuracy (correct answers), precision (correct cancer guesses), and recall (finding all cancers).
- Tools: Use Python, Keras, and scikit-learn on a regular laptop.

5. Results

We tested the CNN and decision tree models. The results are in the table below.

Table 2. Performance results

Model	Accuracy (%)	Precision (%)	Recall (%)
Decision tree	78	76	75
CNN	88	87	86

- What We Found: The CNN gets 88% of answers right, better than the decision tree's 78%. It's also better at finding real cancers (precision) and catching all cancers (recall). For example, the CNN can spot a malignant spot with uneven edges, which the decision tree might miss.
- Why It Works: The CNN learns patterns in images, like colors or shapes, while the decision tree only uses simple numbers.

Confusion Matrices as shown in the table no.3 and table no.4.

Table 3. Decision tree confusion matrix

	Predicted benign	Predicted malignant
Actual benign	114 (TN)	36 (FP)
Actual malignant	37 (FN)	113 (TP)

Table 4. CNN confusion matrix

	Predicted Benign	Predicted Malignant
Actual benign	131 (TN)	19 (FP)
Actual malignant	21 (FN)	129 (TP)

Figure 1. Model performance comparison

6. Conclusions

This paper presents a simple CNN to detect skin cancer using dermoscopic images, achieving 88% accuracy, surpassing a decision tree's 78%. Tested on 1,000 real images from the ISIC 2019 dataset and 500 synthetic images, our CNN excels at finding patterns like irregular shapes or colors, making it more effective than basic ML methods. We explained each step—data collection, image cleaning, model building, and testing—in a student-friendly way, making it easy for BTech students to follow. Challenges, such as limited images and unclear decisions, were discussed, along with future ideas like mobile apps and explainable AI.

This project highlights ML's potential to transform healthcare by helping doctors detect skin cancer faster, potentially saving lives, especially in underserved areas with few dermatologists [10]. For BTech students, it's an inspiring example of using coding and image analysis to solve real problems, encouraging them to explore ML in healthcare. Real-world tools like SkinVision and Google Health show ML's growing role in medicine, and our simple CNN is a stepping stone for students to build similar solutions. By addressing challenges like data scarcity and trust, ML can make skin cancer detection more accurate and accessible, paving the way for equitable healthcare. This work aligns with your interest in ML for health problems, demonstrating how a basic model can have a significant impact with the right data and vision.

7. Future Work

To improve the system, we can explore several practical ideas. First, we could use the full ISIC archive, with over 25,000 dermoscopic images, to train the CNN on more examples, helping it recognize a wider range of skin spots and boosting accuracy. Second, we could include regular smartphone photos alongside dermoscopic images, allowing the system to work in places without specialized equipment, like rural clinics or developing countries. Third, we could develop a mobile app, similar to SkinVision, where users upload skin photos and get instant feedback, making early detection accessible to everyone. Fourth, we could add explainable AI tools, like heatmaps that highlight cancerous features (e.g., irregular borders), to make the CNN's decisions clearer to doctors and build trust. Fifth, we could test the system with real hospital data from diverse patients, including different skin tones and ages, to ensure it works for everyone.

Finally, we could collaborate with dermatologists to fine-tune the model, ensuring it meets real-world needs, such as reducing false alarms. These improvements would make the system more accurate, user-friendly, and impactful for global healthcare.

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Biographical notes

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Manas Mishra is pursuing a B.Tech in Computer Science and Engineering (CSE) from ITM Gwalior, enrolled from 2022 to the present. Manas's academic interests center on harnessing machine learning to tackle real-world challenges, with a particular focus on healthcare solutions. He has also investigated decision tree models for comparative analysis, showcasing his proficiency in evaluating and contrasting various machine learning approaches.