

Melanoma Detection and Classification Using Convolution Neural Network Model

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Abstract

As technology in the field of healthcare advances, so does the need for efficient and accurate detection of skin cancer at earlier stages to improve patient care and reduce workload for medical staff. A novel automated melanoma detection and classification method using deep learning addresses this critical issue by presenting a trustworthy and efficient tool for analyzing dermoscopic images and determining their benign or malignant nature.

This system utilizes advanced deep learning and computer vision technologies based on an efficient and scalable framework. The proposed method utilizes Convolutional Neural Networks (CNNs) that have been implemented using TensorFlow and Keras in Google Colab with the training carried out using an extensive dataset from Kaggle with images of different types of dermoscopic images. The images are preprocessed and augmented to ensure that the system can learn complex patterns and unique features that can be related to melanoma.

The system also provides some key functionalities, such as accurate lesion classification, high feature extraction capability, image analysis, and high performance on different kinds of image samples. The model achieved 95.19% accuracy, thus proving to be highly dependable and useful for decision-making for dermatologists. The system also aids in the early detection of diseases by reducing manual evaluation and minimizing waiting times for diagnosis.

This deep learning technique successfully addresses key issues like the scarcity of skilled dermatologists, human error in interpretation, and the prevalence of melanoma in various parts of the world. The technique enhances the efficacy of medical results by making diagnoses and providing efficient, standardized, and unbiased analysis. The project lays down a solid foundation for further enhancements like multi-class classification of skin lesions, mobile health app integration, real-time environments, and advanced networks like ResNet and EfficientNet.

1. Introduction

Skin cancer ranks among the fastest-growing cancer types globally, with melanoma representing the most severe and potentially fatal variant. When caught early, patient survival chances increase dramatically, yet conventional diagnostic approaches rely extensively on medical expertise, visual examination, and dermoscopy techniques that can lead to variable or subjective results. Recent progress in artificial intelligence and medical imaging has introduced deep learning systems as effective solutions for automated disease identification. Convolutional Neural Networks possess the ability to detect nuanced patterns and visual characteristics in dermoscopic images that might escape human

observation, positioning them as valuable tools for melanoma identification. This project aims to create a deep learning model that can categorize skin lesions as either benign or malignant through dermoscopic image analysis. The system was constructed and trained using TensorFlow and Keras within Google Colab, where it processes image datasets, identifies significant features, and delivers reliable, high-precision predictions. Through automated classification processes, this method assists dermatologists in achieving quicker and more dependable diagnoses, which leads to earlier treatment and improved patient results. The project prioritizes accuracy, dependability, and expandability. It establishes groundwork for future clinical support systems and possible integration into real-time medical screening tools. Skin cancer ranks among the most frequently diagnosed cancers across the globe. Of the different forms that exist, melanoma poses the greatest threat due to its ability to metastasize quickly throughout the body when caught too late. When identified in its early stages, patient survival rates improve dramatically.

Dermatologists typically diagnose melanoma through manual examination using dermoscopy techniques. This approach requires considerable time and relies extensively on the doctor's training and clinical experience. Additionally, people living in rural or isolated regions often struggle to find qualified dermatologists nearby.

Recent progress in Artificial Intelligence and Deep Learning has brought automated diagnostic systems based on medical imaging into focus. Convolutional Neural Networks show particular promise when applied to medical image analysis and classification problems. This study aims to create a CNN-powered system capable of detecting and classifying melanoma cases.

Over the past few years, models built on CNN technology have shown excellent performance in identifying multiple diseases, from pneumonia and breast cancer to brain tumors and skin cancer. CNNs excel at recognizing layered features like edges, textures, shapes, and complex patterns, which makes them particularly good at telling the difference between harmless and cancerous skin lesions.

This study centers on creating an automated system that uses CNNs to detect and classify melanoma through dermoscopic images. The system we propose is designed to sort skin lesions into benign and malignant groups with strong accuracy. Through the use of deep learning methods, this system decreases reliance on manual diagnosis, reduces the chance of human mistakes, and helps dermatologists make better clinical decisions.

In the area of medical imaging, CNN-based models have been effectively used to detect various diseases such as pneumonia, diabetic retinopathy, brain tumors, breast cancer, and skin cancer. These models are capable of processing large volumes of medical image data and identifying patterns which cannot be easily recognized with the naked eye. Thus, the models have shown the capability of achieving the same results as experienced medical professionals.

This research aims to propose a system for the detection and classification of melanoma using Convolutional Neural Networks. The system will utilize the dermoscopic images obtained from the publicly available dataset obtained from the Kaggle website. The images will be preprocessed and resized to the same dimensions to ensure uniformity before being fed into the CNN model. The model will be trained to classify the skin lesion images into two categories: benign and malignant. The implementation of the proposed system has been done using the Python programming language and the TensorFlow and Keras libraries.

Furthermore, the proposed system has the potential to be extended for real-world use cases such as the development of skin cancer detection systems for mobile devices or web-based diagnostic systems. These systems can be used to upload the skin lesion images and obtain diagnostic insights, which can be useful in the early consultation and treatment of the disease.

In conclusion, the integration of deep learning models with medical imaging has the potential to be used for the diagnosis and detection of melanoma and skin cancer. The proposed CNN-based model has shown the capabilities of artificial intelligence in assisting medical practitioners in the faster, accurate, and reliable diagnosis of skin cancer.

Traditionally, melanoma is diagnosed using a technique called dermoscopy, which is a special form of imaging that provides a detailed view of skin lesions. Once a lesion is identified using this technique, it is then sent to a laboratory to undergo a biopsy to determine whether it is malignant or benign. Traditionally, diagnosing melanoma is a tedious process that requires a lot of expertise and experience. Dermatologists find it difficult to differentiate between benign and malignant lesions since most of them display similar characteristics, such as irregular borders, color differences, and texture differences.

2. Related work

Over the past several years, scientists and engineers have investigated numerous machine learning and deep learning approaches for automatically detecting melanoma and other skin lesions. This research has shown substantial advances beyond conventional diagnostic techniques and underscores how well deep neural networks, particularly Convolutional Neural Networks (CNNs), perform in medical image classification applications.

Initial melanoma detection methods relied on conventional machine learning algorithms like Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN), paired with manually designed feature extraction

approaches including texture analysis, color histograms, and shape evaluation. These techniques frequently delivered subpar results because manually crafted features failed to identify the intricate visual characteristics found in dermoscopic images.

When deep learning emerged, scientists moved toward CNN-based approaches because these networks could automatically extract hierarchical features straight from images. Esteva and colleagues used CNN structures that had been pre-trained on ImageNet for classifying skin cancer, reaching performance levels comparable to dermatologists when distinguishing between malignant and benign lesions. Their research revealed that deep features acquired from extensive image collections could effectively transfer to medical images containing subtle pattern differences.

Multiple research teams examined transfer learning methods for melanoma identification. Pre-trained networks including ResNet, VGGNet, Inception, and MobileNet underwent fine-tuning using skin lesion databases such as ISIC (International Skin Imaging Collaboration) and HAM10000. These transfer learning systems delivered excellent accuracy and stability, particularly when paired with data augmentation strategies to handle unbalanced datasets and enhance model adaptability.

Additional studies concentrated on custom CNN designs built specifically for medical imaging applications. These networks frequently included numerous convolution and pooling layers for extracting features at different levels and employed regularization methods like dropout and batch normalization to prevent overfitting. Test results from these custom architectures showed encouraging performance on melanoma classification standards.

Certain research also examined combined approaches that merged CNN feature extractors with conventional classifiers such as SVM to enhance classification outcomes. These systems fed deep features extracted by convolutional layers into machine learning classifiers, resulting in better precision and recall than individual CNN classifiers in some situations.

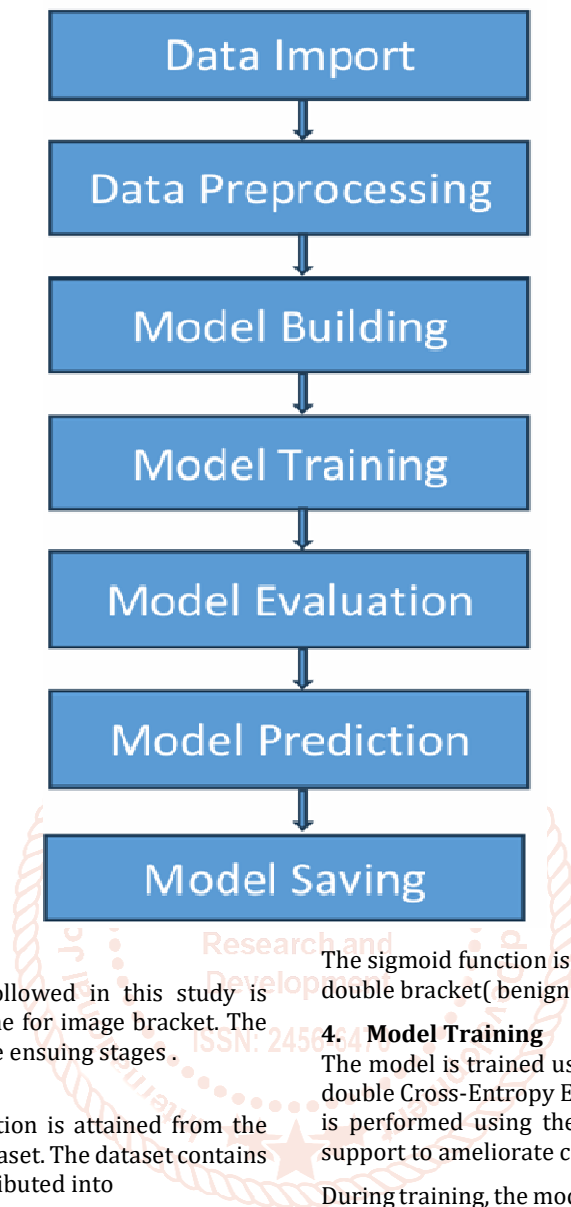
The existing literature review reveals that:

CNN-based deep learning approaches surpass traditional machine learning techniques in melanoma detection because they can identify complex image patterns.

Transfer learning using pre-trained networks substantially enhances model effectiveness on small medical datasets. Data augmentation and preprocessing steps are crucial for managing imbalanced data and preventing overfitting.

Combined systems that merge deep learning with traditional classifiers can deliver additional classification performance gains.

This current study expands on these findings by creating a custom CNN model trained using a labeled melanoma dataset from Kaggle, reaching high classification accuracy and showing an efficient, automated method for early melanoma detection.

Block Diagram :-**3. Research Methodology**

The exploration methodology followed in this study is grounded on a deep literacy frame for image bracket. The complete workflow consists of the ensuing stages .

1. Data Collection

The dataset used in this exploration is attained from the Kaggle Melanoma Skin Cancer Dataset. The dataset contains labeled dermoscopic images distributed into

Benign lesions nasty lesions

These images serve as input data for training and testing the CNN model.

2. Data Preprocessing

Data preprocessing is an important step to ameliorate model performance and insure thickness. The following preprocessing ways are applied

Resizing all images to 224×224 pixels Normalizing pixel values to gauge between 0 and 1 Splitting dataset into training and testing sets

Applying data addition(if used) to ameliorate conception

Preprocessing helps reduce noise and ensures invariant input size for the CNN model.

3. Model Development

A Convolutional Neural Network(CNN) armature is designed for double bracket. The CNN model includes Convolutional layers for point birth ReLU activation functions Max pooling layers for dimensionality reduction Flatten subcaste to convert point charts into a vector Completely connected(thick) layers Affair subcaste with Sigmoid activation function

The sigmoid function is used because the problem involves double bracket(benign vs nasty).

4. Model Training

The model is trained using Optimizer Adam Loss Function double Cross-Entropy Evaluation Metric Accuracy Training is performed using the Google Colab platform with GPU support to ameliorate computational effectiveness.

During training, the model learns to prize important features similar as shape, texture, and color variations that help separate nasty lesions from benign bones.

5. Model Evaluation

After training, the model is estimated using the test dataset. The following performance criteria are used Accuracy

Precision Recall

F1- Score

Confusion Matrix

The proposed model achieves an delicacy of 95.19, demonstrating strong bracket performance.

6. Model Deployment

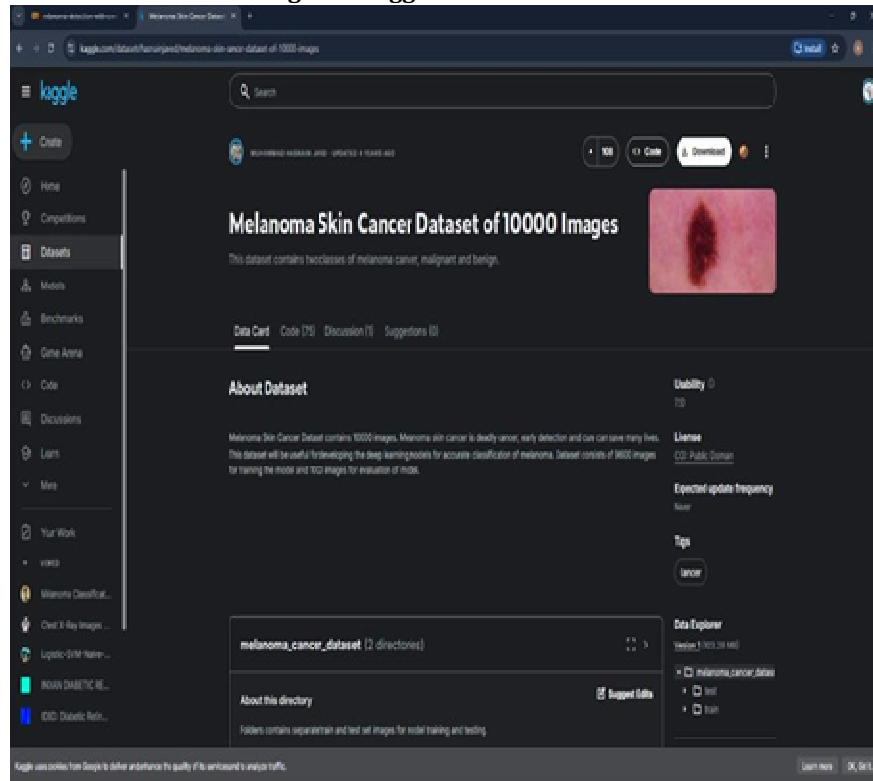
The trained model is saved for unborn use. It can be integrated into

A web- grounded operation

A mobile operation

Clinical decision support systems

This enables real- time carcinoma discovery and automated opinion backing.

Figure : Kaggle Dataset Window

4. Implementation

In this chapter, the practical application of the suggested melanoma detection system is discussed. This includes a description of the process of preparing the data, creating the CNN model, as well as the prediction process of the system, all of which are carried out using Python, TensorFlow/Keras, and Google Colab.

1.1 Coding Explanation

The code for this implementation comprises various steps, from loading the data to making the prediction. The following are the different parts of the code used to create this model.

1.2 Importing Required Libraries

The very first part of the code is to import all the required libraries that are to be used for this deep learning model implementation in Python.

- TensorFlow / Keras → for building CNN
- NumPy → for numerical computations
- Matplotlib → for plotting graphs
- OpenCV / PIL → for image processing
- scikit-learn → for evaluation metrics

All these libraries are the technical part of this model implementation.

1.3 Loading the Dataset

The dataset is to be downloaded from Google Drive or directly from Kaggle and stored in folders:

- /train/benign
- /train/malignant
- /test/benign
- /test/malignant

The images in this case are classified based on their type. The dataset generator helps in loading the images in batches for efficient preprocessing.

1.4 Data Preprocessing

The images need to be preprocessed for efficient training:

- Resize: All images need to be resized to 224x224 pixels.
- Normalize: The pixel values need to be normalized from 0-255 to 0-1.
- Augment: Techniques such as rotation, flipping, zooming, etc., can be employed for efficient training.

Some of the operations performed during this phase include:

- ImageDataGenerator(rescale=1./255)
- rotation_range=20
- horizontal_flip=True

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- ImageDataGenerator(rescale=1./255)
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- horizontal_flip=True
- Accuracy – proportion of accurate predictions
- Precision – proportion of accurate positive predictions

- Recall – ability to detect melanoma cases
 - F1-score – balance of precision and recall
 - Confusion matrix – ratio of accurate vs. false predictions
- The model in this project achieved:
- ❖ 95.19% accuracy

with high precision, recall, and F1-score balance.

1.6 Model Saving and Loading The model is saved in:

- .h5 format for portability
- .keras for future use in TensorFlow

Saving the model enables future use for testing, deploying, or integrating it in mobile/web applications.

1.7 Prediction on New Images To use this system, simply:

1. Upload an image
 2. Preprocess it
 3. Input it to the pre-trained model
 4. Output:
- Benign or Malignant
 - Confidence level

This illustrates the usability of this melanoma detection system.

1.8 Training & Evaluation Screenshots

You will include your screenshots in your thesis document. Below are descriptions for your screenshots to be included in your thesis document.

1.9 Training Screenshot Explanation The screenshot contains:

- Evolution of training accuracy per epoch
- Validation accuracy
- Loss plots
- Training logs in Google Colab

The metrics show how well the model learned from epoch to epoch.

1.10 Accuracy and Loss Curves You will provide graphs showing:

- Accuracy of validation data against epochs
- Loss of training data against epochs
- Loss of validation data against epochs

The above graphs visually verify:

- No signs of overfitting
- Smooth training curves
- Stability of the model

1.11 Confusion Matrix Screenshot The above screenshot shows:

- True positives (malignant detected correctly)
- True negatives (benign detected correctly)
- False positives
- False negatives

A basic understanding of classification is achieved.

Final Output Screenshots:

Melanoma



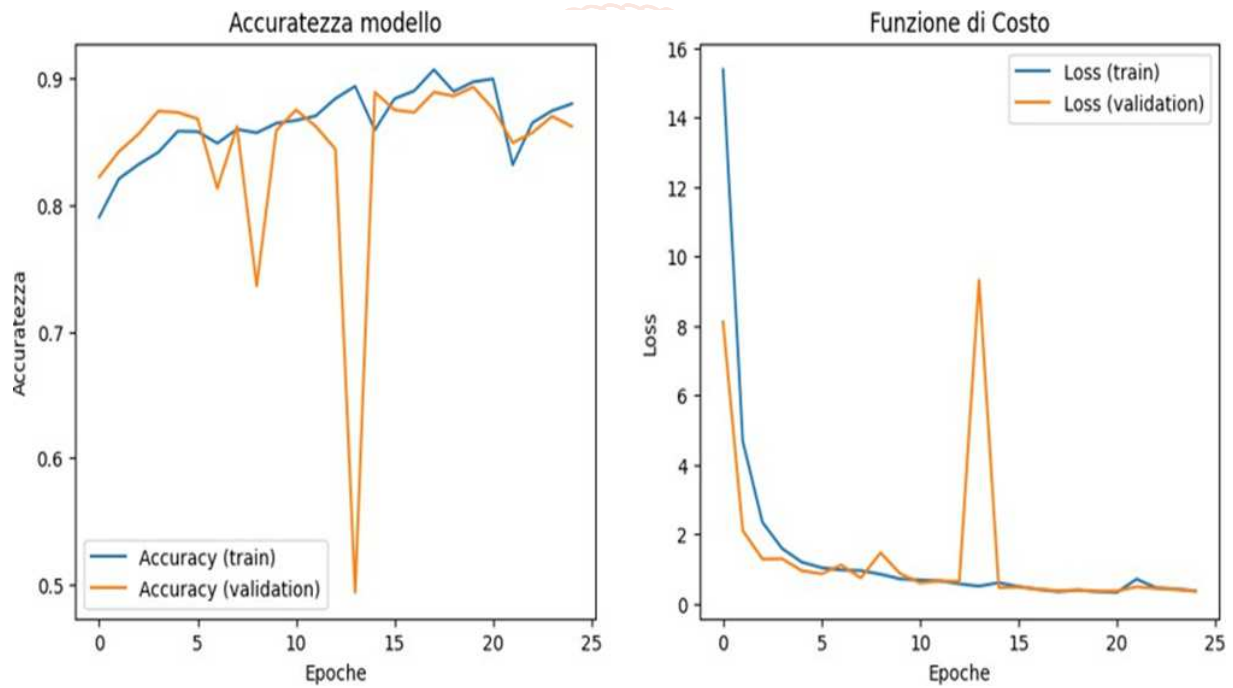
Solar Lentigo



Figure: Uploaded dermoscopic image



Figure : Accuracy and Loss



Final Metrics Summary

Summary Metrics Table	
Metric	Value
Accuracy	95.19%
Precision	0.9615
Recall	0.9615
F1-Score	0.9615
ROC-AUC	0.9854

Cancer at the initial stages. The system designed in the project uses a Convolutional Neural Network (CNN) to classify the images obtained from dermoscopy as either benign or malignant with a high degree of accuracy.

During the course of implementing the project, several steps have been taken:

- Obtaining the image datasets related to melanoma
- Developing a systematic CNN architecture
- Training the system using TensorFlow/Keras
- Checking the performance of the system using various parameters
- Testing the system using unseen images

The accuracy level obtained from the system was 95.19%, proving the reliability of the system. It is evident from the results that the system has a balanced precision, recall, and F1-score value.

1. Future Scope

Though the developed system is performing well, there are many opportunities to improve and extend the project in the future. The following changes and extensions can be made to the system to make it powerful and deployable:

1.1 Advancement in Deep Learning

Future research can be carried out using advanced deep learning architectures such as:

- ResNet, DenseNet, EfficientNet
- Vision Transformers (ViT)
- Hybrid CNN and Transformers

These architectures can improve the accuracy and generalization capacity of the model.

1.2 Multi-Class Skin Lesion Classification

The system is currently performing binary-classification.

It can be extended to classify multiple types of skin conditions such as:

- Melanoma
- Basal Cell Carcinoma
- Actinic Keratosis
- Benign Keratosis
- Vascular lesions
- Dermatofibroma

This can be achieved by using multiple classes in the neural network.

1.3 Deployment as Mobile and Web Applications

The developed model can be deployed as part of the following applications:

- Android and iOS mobile applications
- Web applications
- Cloud-based AI Diagnostic Applications

This can be used to perform real-time melanoma detection anywhere in the world.

1.4 Real-Time Camera-Based Detection

By using the OpenCV and TensorFlow Lite libraries, the model can be modified to perform real-time skin lesion detection using the camera.

1.5 Explainable AI (XAI) Integration

The Grad-CAM and LIME methods can be employed to pinpoint the areas of the lesion that contributed to the prediction.

- Trust
- Interpretability
- Clinical acceptance

1.6 Increase Data Diversity and Size

The accuracy of the model can be enhanced through the following strategies:

- Utilizing the ISIC, HAM10000, and Kaggle datasets
- Using images with increased diversity from different demographics
- Applying complex image augmentation and generation using GANs

1.7 Clinical Validation

Future developments can be achieved through the following strategies:

- Working with dermatologists
- Using real images

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