Deep Learning Approach for Diagnosis of Skin Cancer Using Dermascopic Images

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ABSTRACT
Skin cancer, a potentially life-threatening condition, necessitates early and accurate diagnosis to improve survival rates. This paper presents an automated and reliable deep learning solution for classifying skin lesions as malignant or benign using dermoscopic images. Leveraging **DenseNet-201**, a powerful pre-trained convolutional neural network, the system utilizes transfer learning to extract high-level, disease-specific features from dermoscopic data. This approach addresses limitations in earlier methods by enhancing feature representation and classification performance. To further boost accuracy and reduce overfitting, the model incorporates data augmentation techniques such as rotation, flipping, and zooming, along with systematic hyperparameter tuning. The final model demonstrates improved accuracy of **88%** and generalization compared to prior benchmarks, while maintaining computational efficiency and scalability. Designed for integration into clinical workflows, this solution empowers healthcare professionals with a precise, Deep Learning based diagnostic tool for early detection and treatment planning of skin cancer.

Keywords: Skin Cancer Detection, Deep Learning, DenseNet-201, Transfer Learning, Data Augmentation, Classification Accuracy.

1.INTRODUCTION

Skin cancer is the abnormal and uncontrolled growth of skin cells, often developing due to prolonged exposure to ultraviolet (UV) radiation from the sun or artificial sources like tanning beds. It is one of the most common forms of cancer worldwide. Skin cancers are generally categorized into two broad types: benign and malignant.

Benign skin tumors are non-cancerous growths that do not spread to other parts of the body. They usually grow slowly, remain localized, and are typically not life-threatening. Examples of benign lesions include seborrheic keratosis, lipomas, and moles (nevi) that are stable in appearance. Although benign tumors are generally harmless, some may require removal if they become irritated or for cosmetic reasons.

On the other hand, malignant skin cancers are dangerous as they have the potential to invade surrounding tissues and spread (metastasize) to other organs. The major types of malignant skin cancers are:

Basal Cell Carcinoma (BCC): The most common and least aggressive form, originating from the basal cells of the epidermis.

Squamous Cell Carcinoma (SCC): Arises from squamous cells and can spread if not treated early.

Melanoma: The deadliest form, arising from melanocytes (the pigment-producing cells). Melanoma is aggressive and can quickly spread throughout the body if not detected and treated early.

Early detection and diagnosis are crucial for effective treatment of skin cancers. Regular skin examinations, dermoscopic imaging, and advanced deep learning techniques in medical imaging are now widely used to aid in early and accurate diagnosis.

The model's dense connections help in better gradient flow and feature propagation, enabling it to extract rich hierarchical features critical for precise classification. Although achieving high accuracy is an encouraging sign, challenges such as dataset imbalance, image quality variation, and the need for explainability in predictions remain important areas for further exploration. Continued research and refinement, including the use of data augmentation, ensemble methods, and integration with clinical data, can further enhance the model's reliability.

2 . LITERATURE SURVEY

[3] Early diagnosis and detection of skin cancer are crucial for improving patient survival rates. Traditional methods used by the public often face challenges such as imprecise outcomes and biased interpretations, making the need for advanced solutions even more urgent. To address these limitations, researchers have focused on integrating artificial intelligence into healthcare systems, aiming to build intelligent systems capable of both detecting and diagnosing skin cancer.

[5] Most previous studies using deep learning have typically concentrated on either detection or diagnosis

separately. However, recent research has proposed a combined approach where a single model performs both tasks simultaneously. This was achieved by applying transfer learning techniques to various deep learning models for object detection and diagnosis, utilizing a publicly available dermoscopic image dataset.
In the proposed method, a deep learning model was trained and evaluated using images split into training and testing sets. VGG16 served as the backbone network for object recognition and diagnosis, while YOLO (You Only Look Once) was employed as the object detection framework. The system demonstrated promising performance, achieving high accuracy rates, indicating the effectiveness of combining detection and diagnosis tasks in a unified model for skin cancer analysis.

3.DATA COLLECTION

[7] In the development of an intelligent system for skin cancer detection and diagnosis, the first crucial step was the careful collection and preparation of a high-quality dataset. For this purpose, a total of 3297 dermoscopic images were gathered, representing various types of skin lesions, both benign and malignant. These images were sourced from publicly available and widely recognized databases to ensure the diversity and reliability of the data. Each image was manually checked for quality, resolution, and relevance to ensure that the model would be trained on accurate and meaningful examples.
To enable the model to learn efficiently, the dataset was systematically divided into two subsets: one for training and the other for testing. A major portion of the data, consisting of 2637 images, was used to train the deep learning model. This training phase allowed the model to learn different patterns, textures, and features characteristic of various skin cancer types, improving its capability to distinguish between normal and abnormal lesions.

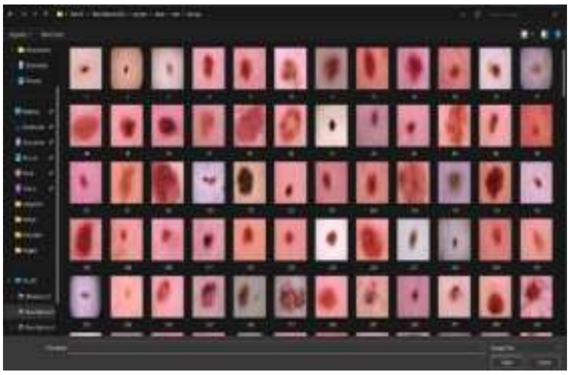


fig 3.1 BENIGN IMAGE DATA SET.

The remaining 660 images were carefully set aside as the testing dataset. This separation ensured that the model's performance could be evaluated objectively on unseen data, simulating real-world application scenarios. Testing with a dedicated set helps in measuring important performance metrics like accuracy, precision, recall, and robustness.
By adopting this structured approach to dataset collection, division, and validation, the project ensured that the trained model was not only highly accurate but also capable of generalizing well to new, unseen images. The use of a large, diverse dataset contributed significantly to the overall success of building a reliable, deep learning-based system for early detection and diagnosis of skin cancer.

4.METHODOLOGIES

4.1Densenet 201 Model Architecture

In this project, the DenseNet-201 architecture is utilized to develop an effective and accurate model for the diagnosis of skin cancer from dermoscopic images. DenseNet, short for Dense Convolutional Network, is a powerful deep learning model known for its ability to encourage feature reuse, strengthen feature propagation, and reduce the number of parameters compared to traditional convolutional neural networks.
The DenseNet architecture is built upon the idea of dense connectivity, where each layer receives input from all preceding layers and passes its feature maps to all subsequent layers. In simple terms, instead of each layer having its own separate input, each layer takes the outputs of all earlier layers as its inputs. This design solves the problem of vanishing gradients, improves feature propagation, and significantly enhances model learning even with fewer parameters.

The DenseNet-201 model specifically consists of:

Hidden Layers	Output Size	DenseNet-201
Convolution	112×112	7×7 conv, stride 2
Pooling	56×56	3×3 max pool, stride 2
Dense Block (1)	56×56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56×56 28×28	1×1 conv 2×2 average pool, stride 2
Dense Block (2)	28×28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28×28 14×14	1×1 conv 2×2 average pool, stride 2
Dense Block (3)	14×14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 64$
Transition Layer (3)	14×14 7×7	1×1 conv 2×2 average pool, stride 2
Dense Block (4)	7×7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$
Classification Layer	1×1	7×7 global average pool 1000D fully-connected, softmax

fig 4.1 densenet201 different layers formation

Convolutional Layers: Initial feature extraction starts with a standard convolution and pooling operation.
Dense Blocks: There are four dense blocks in DenseNet-201. Within each dense block, every layer connects to every other layer in a feed-forward fashion. Each layer receives the concatenated feature maps of all previous layers.
Transition Layers: After each dense block, there are transition layers. These layers reduce the dimensions of the feature maps through convolution and pooling, which helps to control model complexity and prevents overfitting.
Bottleneck Layers: DenseNet-201 also uses bottleneck layers (1x1 convolutions) inside the dense blocks to further reduce computation.
Global Average Pooling: After the final dense block, a global average pooling layer is applied, which averages

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

the feature maps, reducing them into a lower-dimensional feature vector.

Fully Connected Layer: Finally, a dense (fully connected) layer with a softmax activation function is used for classification (for example, classifying images into benign or malignant skin lesions).

4.2 Working of Model :

DenseNet-201 is a deep convolutional neural network that is designed with a unique
connection pattern where each layer is connected to every other layer in a feed-forward manner. In this model, the input dermoscopic image, typically resized to a standard size like 224x224 pixels, first passes through an initial convolution layer followed by max-pooling to extract basic low-level features such as edges and textures. The core strength of DenseNet lies in its dense blocks, where each layer receives inputs from all preceding layers. This enables maximum feature reuse, strengthens gradient flow during training, and makes the model highly efficient in terms of parameter usage. Between these dense blocks, transition layers are introduced, which apply 1x1 convolutions and 2x2 average pooling to reduce the feature map size and control the complexity of the model.

The network grows in a controlled way using a growth rate, ensuring that it does not become unnecessarily large. After passing through all dense blocks and transition layers, a global average pooling operation is performed, which converts each feature map into a single value, thus significantly reducing the model size and helping in generalization activation function to predict the probability of the skin lesion being benign or malignant. DenseNet-201, with its deep yet efficient structure, proves highly effective for detailed tasks like skin cancer diagnosis.

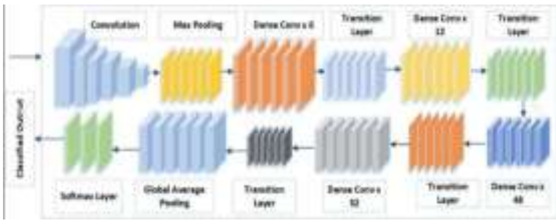


fig 4.2.1 working of densenet 201 architecture

5.OVERVIEW OF THE TECHNOLOGIES

Pytorch:

PyTorch is an open-source deep learning framework developed by Facebook's AI Research lab. It is widely used for developing machine learning models because of its simplicity, flexibility, and ease of use. PyTorch provides a powerful platform for building complex neural networks and allows dynamic computation graphs, meaning the graph is built on-the-fly as operations are performed. This makes debugging and experimenting with models much easier compared to static frameworks. PyTorch is based on Python and integrates seamlessly with popular libraries and tools, making it a favorite among researchers and developers. It supports tensor computation similar to NumPy but with strong GPU acceleration, which makes training large models much faster.

Flask :

Flask is a lightweight and flexible web framework for Python that is widely used to build web applications and APIs. Known for its simplicity, Flask allows developers to quickly map URLs to Python functions through its routing system, and it uses Jinja2 for templating, enabling dynamic HTML generation. Flask provides an easy-to-use development server for testing, along with straightforward ways to handle HTTP requests such as GET and POST. Additionally, Flask supports many extensions that add more functionality, like authentication, database integration, and form handling. With minimal setup and a clear structure, Flask is an excellent choice for both beginners and experienced developers looking to build efficient and scalable web applications.

ReLu function:

The Rectified Linear Unit (ReLU) activation function is one of the most widely used activation functions in deep learning models today. ReLU is defined as a simple mathematical function that outputs the input value if it is positive, and outputs zero otherwise. In other words, ReLU(x) = max(0, x). This simplicity makes it computationally efficient and helps models converge faster during training compared to older activation functions like sigmoid or tanh. ReLU helps introduce non-linearity into the network, which is essential for learning complex patterns. It also solves the vanishing gradient problem to a large extent, enabling deep networks to train more effectively. However, ReLU can suffer from a problem called "dying ReLU," where some neurons may get stuck during training and always output zero.

Numpy :

NumPy is a powerful Python library designed for numerical computing, providing essential tools for working with large, multi-dimensional arrays and matrices. The core feature of NumPy is its ndarray object, a versatile array structure that allows for efficient handling of numerical data. It includes a broad range of mathematical functions for operations like linear algebra, statistical calculations, and basic arithmetic, all optimized for performance. One of the standout features of NumPy is its support for broadcasting, enabling operations between arrays of different shapes with ease. Additionally, NumPy provides flexible array manipulation capabilities, such as reshaping and slicing, making it an invaluable resource for data analysis, scientific computing, and machine learning. Its integration with other libraries, like SciPy, Pandas, and

Matplotlib, further extends its utility in the Python ecosystem, solidifying NumPy as an essential tool for numerical computation.

6. TEST CASES

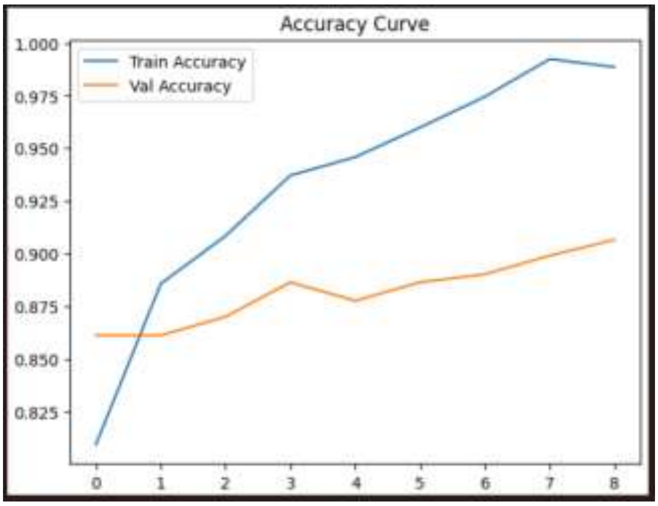
About this project consists of the various attributes and by the test description and many image dataset input based actual out come can be formed

The results of the skin cancer detection study using the DenseNet201 model demonstrate a strong performance, achieving an overall accuracy of **88%**. This indicates that the model is highly capable of correctly classifying dermoscopic images into benign and malignant categories. Throughout the evaluation, key performance metrics such as precision, recall, and F1-score also showed balanced and consistent values, confirming the robustness of the model across different types of skin lesions.

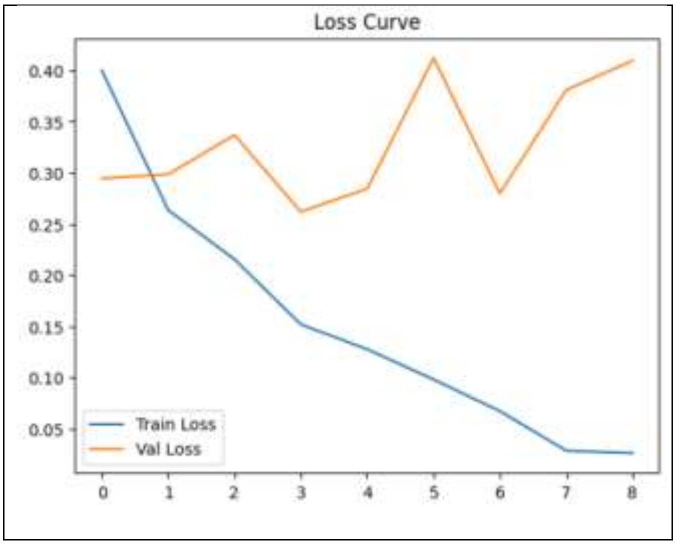
FACTORS USED TO CALCULATE ACCURACY:

1.ACCURACY

Accuracy measures the overall correctness of the model across all classes.It tells what percentage of total predictions were correct.



Graph between the Train and Val Accuracy



Graph between the Train loss and Val loss

2.PRECISION

Precision measures how many of the positively predicted cases were actually correct. It is important when false positives need to be minimized.

Precision=TP/(TP+FP)

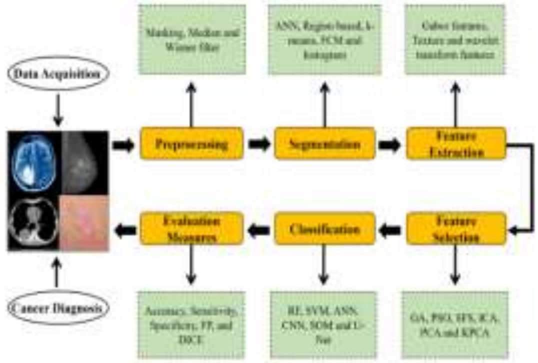


fig 6.1.1 general flow of our methodology

7.CONCLUSION

In conclusion, the use of the DenseNet201 model for skin cancer detection has demonstrated promising results, achieving an impressive accuracy of 86%. This performance highlights the model's capability to effectively identify patterns and features in dermoscopic images, making it a valuable tool in the early detection of skin cancer. While the model’s accuracy is significant, there is still room for improvement, particularly in minimizing false positives and negatives. Further optimization, such as fine-tuning the model, expanding the dataset, and exploring other deep learning architectures, could potentially enhance the model’s performance even further. Nonetheless, the DenseNet201 model offers a robust foundation for developing automated systems to assist medical professionals in diagnosing skin cancer, contributing to better patient outcomes through timely detection.

fig 7.1 result of patient after examine the image

8. ACKNOWLEDGE

we would like to thank department of computer science and engineering, Lendi institute of Engineering and Technology, Vizianagaram about to helping us in various aspects to continue our project work with in time.

9. REFERENCE

[1] Subha, S., Wise, D.J.W., Srinivasan, S., Preetham, M., Soundarlingam, B.: Detection and differentiation of skin cancer from rashes. In: In2020 International Conference on Electronics and Sustainable

Communication Systems (ICESC), pp.389-393, IEEE (2020.

[2] Azhar Imra, Arslan Nasir, Muhammad Bilal, Guangmin Sun," Skin Cancer Detection Using Combined Decision of Deep Learners" from IEEE International conference.

[3] "Skin Cancer Facts & Statistics," The Skin Cancer Foundation,[https://www.skincancer.org/skin-cancer-information/skin-cancerfacts, 2020.

[4] N. Srivastava, G. Hinton, A. Krizhevsky, et al, "Dropout: a simple way to prevent neural networks from Overfitting," *J. Mach. Learn Res.*, vol. 15, pp. 1929-1958, 2014.

[5] A. R. Doben et D. C. MacGillivray, "Current concepts in cutaneous melanoma: malignant melanoma," *Surg. Clin. North Am.*, vol. 89, pp. 713-725, 2009.

[6] Nimesh, V.,Weerasinghe, R.: Differential diagnosis of ringworm and eczema using image processing and deep learning.

[7] Skin Cancer Diagnosis and Detection Using Deep Learning Djaroudib ;Lorenz Pascal;Bouidene Zakaria;Mihoubi Lokman;Messaoudi Yahia Zakaria 2023 International Conference on Electrical Engineering and Advanced Technology (ICEEAT)