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# DEEP LEARNING-BASED DIAGNOSIS FOR SKIN DISEASE PREDICTION

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**Abstract-** Skin diseases are increasingly prevalent, and their accurate diagnosis remains challenging due to the complexity of medical imaging and the diversity of conditions. Existing systems primarily rely on Generative Adversarial Networks (GANs) for skin disease prediction, but they face stability issues and inconsistencies during training. Additionally, the reliance on synthetic data generation often results in less accurate predictions when the generated images fail to fully capture real-world variability. To overcome these limitations, the proposed system employs EfficientNetB0, a deep learning model optimized for medical image analysis. EfficientNetB0 uses a compound scaling method to balance depth, width, and resolution, enabling efficient feature extraction while maintaining high accuracy. Its lightweight architecture allows for faster processing without compromising performance, making it ideal for skin disease classification. By leveraging EfficientNetB0, the system enhances early detection, improves diagnostic Precision, and reduces misclassification risks, ultimately supporting better patient outcomes in clinical practice.

***Keywords: Skin disease diagnosis, EfficientNetB0, deep learning, medical imaging, feature extraction, classification, prediction accuracy, healthcare AI, early detection, diagnostic precision.***

## *I. Introduction:*

Skin diseases range from benign conditions to malignant cancers, making accurate diagnosis crucial for effective treatment. Actinic keratosis is a precancerous skin lesion caused by prolonged exposure to sunlight, often appearing as rough, scaly patches on sun-exposed areas. If not treated, it can develop into squamous cell carcinoma (SCC), a common type of skin cancer that affects the outer skin layers and typically presents as red, scaly, or ulcerated patches. Similarly, basal cell carcinoma (BCC) is the most frequently diagnosed skin cancer, often manifesting as pearly or waxy bumps. Although BCC rarely spreads, early detection is essential to prevent extensive tissue damage. While some skin conditions are non-cancerous, they can closely resemble malignant lesions, making precise classification necessary. Dermatofibroma is a firm, slow-growing nodule that is harmless but may be mistaken for a cancerous growth. Nevus (mole) is another common

 

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skin lesion made up of melanocytes, some of which have the potential to develop into melanoma, an aggressive form of skin cancer characterized by irregularly shaped, dark lesions. Additionally, pigmented benign keratosis is a non-cancerous skin condition that can be confused with melanoma due to its dark pigmentation. Other skin disorders include seborrheic keratosis, which appears as waxy, wart-like growths that, despite being benign, may resemble cancerous lesions. Vascular lesions, such as hemangiomas and angiomas, develop from abnormal blood vessel growth and typically present as red or purplish skin marks. Given the visual similarities among these conditions, advanced deep learning models like EfficientNetB0 play a key role in distinguishing between benign and malignant lesions, improving diagnostic accuracy, enabling early detection, and supporting better patient care.

### a. *EfficientNetB0:*

EfficientNetB0 is a deep learning model designed for image classification, known for its ability to achieve high accuracy while maintaining computational efficiency. It was developed using a compound scaling method, which optimally balances network depth, width, and resolution to improve performance. Unlike traditional convolutional neural networks (CNNs) that scale arbitrarily, EfficientNetB0 applies a systematic approach to scaling, ensuring better feature extraction without significantly increasing computational complexity. This makes it an ideal choice for medical image analysis, where accurate classification of conditions like skin diseases is essential. One of the key strengths of EfficientNetB0 is its lightweight architecture, which allows for faster processing without compromising accuracy. It uses mobile inverted bottleneck convolution (MBConv) layers, which enhance feature extraction while reducing the number of trainable parameters. This efficient structure enables the model to capture intricate details in medical images, making it well-suited for tasks that require distinguishing between visually similar conditions, such as benign and malignant skin lesions. Additionally, EfficientNetB0 incorporates squeeze-and-excitation (SE) blocks, which refine feature representations by emphasizing the most relevant information, further boosting its classification performance. Due to its efficient design and strong generalization capabilities, EfficientNetB0 has been widely adopted in healthcare applications, particularly in disease diagnosis through medical imaging. Its ability to maintain high accuracy with lower computational demands makes it suitable for deployment in resource-constrained environments, such as mobile health applications or real-time diagnostic tools. By leveraging EfficientNetB0, healthcare professionals can improve early detection and diagnosis, ultimately enhancing patient outcomes through faster and more reliable medical image analysis.

### b. *Architecture diagram of EfficientNetB0:*

EfficientNetB0 is a deep learning model designed for image classification, utilizing a unique compound scaling approach to optimize performance while

 

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minimizing computational costs. Its architecture is built around mobile inverted bottleneck convolution (MBConv) layers, which improve feature extraction efficiency while reducing the number of parameters. Additionally, it integrates squeeze-and-excitation (SE) blocks, which enhance the model's ability to focus on important features by recalibrating channel-wise activations. These design choices enable EfficientNetB0 to achieve high accuracy while maintaining a lightweight structure, making it well-suited for tasks such as medical image analysis and skin disease classification. The model follows a hierarchical design, beginning with an initial convolutional layer, followed by a series of MBConv blocks that progressively extract more complex patterns from input images. Unlike traditional CNNs that arbitrarily scale layers, EfficientNetB0 uses depthwise separable convolutions, which significantly reduce computational complexity while preserving essential details. The final stages of the network include a global average pooling layer, a fully connected layer, and a softmax activation function, which classifies images into predefined categories. This structured approach ensures efficient processing while maintaining high classification accuracy.

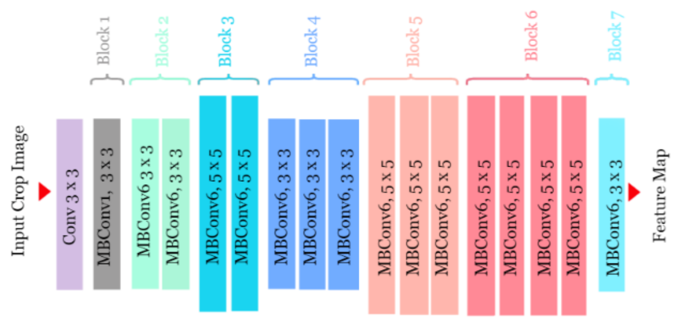


***Fig.1 Architecture of Efficientnet***

A key innovation of EfficientNetB0 is its compound scaling strategy, which adjusts the model's depth (layers), width (channels per layer), and resolution (input image size) in a balanced manner. Instead of increasing only one aspect, this technique scales all three dimensions proportionally, ensuring optimal performance without excessive computational demands. This efficiency makes EfficientNetB0 a preferred choice for real-world applications, particularly in medical imaging, where precise classification and minimal computational overhead are crucial for timely and accurate diagnoses.

## ***II. Literature survey:***

***[1] Kuldeep Vayadande Amol A. Bhosle , Rajendra G. Pawar [1]*** Skin diseases, ranging from mild conditions like acne to severe disorders such as melanoma, pose significant challenges in healthcare due to their diverse presentations. Accurate diagnosis is essential to ensure effective treatment and prevent complications. However, traditional diagnostic methods, which rely on visual examination by dermatologists, can be subjective and prone to errors. This has led to the growing adoption of artificial intelligence (AI) and machine learning (ML) for improving diagnostic accuracy and consistency. AI-driven models, particularly K-Nearest Neighbors (KNN) and Support Vector Machines (SVM), are widely used for classifying skin diseases based on extracted features from medical images. These models help differentiate between conditions by identifying

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patterns within the data. More advanced techniques, such as Convolutional Neural Networks (CNNs), have become integral to dermatology. CNNs specialize in analyzing image data, effectively detecting, classifying, and segmenting skin lesions. Their ability to recognize intricate visual patterns makes them highly effective for early diagnosis and treatment planning. ***[2] Syed Inthiyaz , Baraa Riyadh Altahan · Sk Hasane Ahammad [2]***

Diagnosing skin diseases is challenging due to the complexity of visual patterns in dermatological conditions. Early and accurate detection is essential for effective treatment and better patient outcomes. Artificial intelligence (AI) has become a valuable tool in dermatology, utilizing advanced techniques to analyze large datasets. AI-driven methods extract significant features from medical images, aiding in precise classification of skin diseases, including tumors. This study explores various AI techniques, focusing on image processing, feature extraction, and deep learning models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Different models, including Support Vector Machines (SVM) and Random Forest, were tested on datasets like the Coimbra dataset from UCI. Among them, RNNs achieved a 92% accuracy, demonstrating strong potential in tumor detection. Their ability to process sequential data makes them highly effective for dermatological diagnosis. This study highlights AI's role in reducing diagnostic errors, accelerating detection, and ensuring timely treatment for skin disease patients. ***[3] Ling-Fang Li; Xu Wang; Wei-Jian Hu; Neal N. Xiong; Yong-Xing Du [3]*** Deep learning has emerged as a key tool in medical research, particularly for diagnosing skin diseases, which are visually distinguishable compared to other conditions. The application of deep learning in skin disease recognition has gained significant attention due to its potential for accurate and efficient diagnosis. This study reviews 45 research efforts since 2016, analyzing various aspects such as disease classification, datasets, data processing, augmentation techniques, deep learning models, frameworks, evaluation metrics, and overall model performance. Additionally, the study compares traditional and machine learning-based approaches for diagnosing and treating skin diseases. It highlights the advancements in this field and identifies four potential research directions for future exploration. Findings indicate that deep learning methods outperform dermatologists and other computer-aided techniques, particularly when multiple models are combined. The study emphasizes that integrating deep learning frameworks enhances recognition accuracy, making it a promising approach for improving skin disease diagnosis and patient care.

***[4]DasariAnantha Reddy , Swarup Roy , Sanjay Ku mar , Rakesh Tripathi [4]*** Diagnosing skin disorders through visual inspection is challenging due to overlapping lesion characteristics, skin texture variations, hair interference, and poor lighting conditions. These factors make accurate diagnosis difficult, even for experienced dermatologists. While Computer Vision (CV) and Machine Learning (ML) have improved lesion detection, they still face limitations in handling complex artifacts, highlighting the need for more advanced diagnostic frameworks.

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The proposed detection framework addresses these challenges through a multi-step process. It begins with lesion segmentation using Optimized Region Growing (ORG) and Grey Wolf Optimization (GWO), which effectively isolate diseased areas from healthy skin. Next, feature extraction is performed using the Gray Level Co-occurrence Matrix (GLCM) for texture patterns and the Weber Local Descriptor (WLD) for edge details. An autoencoder then refines these features by reducing redundancy. Finally, a Convolutional Neural Network (CNN) classifies lesions based on extracted features, enhancing accuracy in skin disease diagnosis. ***[5] Kuldeep Vayadande, Om Lohade, Sumit Umbare [5]*** Deep learning has become a vital tool in diagnosing skin diseases, which often exhibit distinct visual traits. These conditions affect people worldwide, yet early symptoms can be subtle, leading to delayed diagnosis and treatment. Automated, image-based diagnostic systems help address this challenge, particularly in remote or underserved areas with limited access to dermatologists. By enabling early detection, these systems improve treatment outcomes and reduce disease progression. To meet this need, a multi-class deep learning model was developed to differentiate between healthy and diseased skin. Trained on a diverse dataset, the model accurately classifies various skin conditions and assesses their severity. Its optimized architecture enhances diagnostic precision, assisting healthcare professionals in providing timely and effective treatments. This AI-driven approach not only supports medical experts but also improves accessibility to dermatological care, reducing healthcare burdens and contributing to better global health management by ensuring early and reliable disease detection. ***[6] Somil Gambhir; Sanya Khanna; Priyanka Malhotra [6]*** Lumpy skin disease is a contagious viral infection affecting cattle, raising concerns among nations due to its impact on livestock health and the agricultural economy. Climate plays a crucial role in the transmission and spread of the disease, influencing infection patterns across different regions. By leveraging machine learning, researchers can analyze various climatic factors to determine the likelihood of disease occurrence in specific areas. This approach enhances early detection and prevention efforts, helping farmers and authorities take proactive measures to protect cattle. In this study, machine learning algorithms, including Adaboost, K-nearest neighbors, decision trees, and random forests, were used to predict lumpy skin disease. The model achieved a high accuracy of 90% and an F1 score of 1.0, demonstrating its effectiveness in identifying disease-prone regions. Among these algorithms, decision trees proved particularly useful for predicting infection based on geospatial and climatic data, making them valuable for monitoring disease outbreaks.

### *A. Architecture diagram of proposed system:*

The architectural framework represents a deep learning-driven system for skin disease classification, structured into two key phases: Training Phase and Testing Phase. In the Training Phase, skin disease images are sourced from Kaggle and processed through multiple enhancement techniques, including

 

Region of Interest (ROI) extraction, grayscale conversion, noise reduction, and contrast adjustment, ensuring image clarity. Following this, feature extraction is performed using edge detection, histogram-based features, and wavelet transform to emphasize essential patterns.

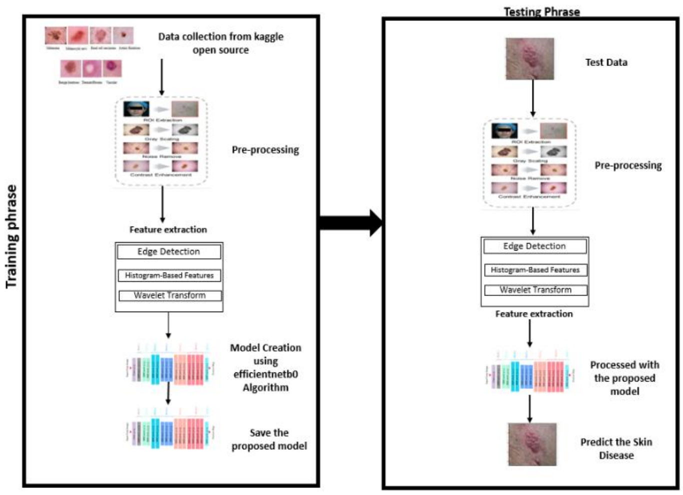


*Fig.2 Architecture Of proposed system*

These refined features are then used to develop a deep learning model utilizing the EfficientNetB0 algorithm, which is optimized for precise disease classification. The trained model is stored for subsequent use. During the Testing Phase, a new skin image undergoes the same pre-processing and feature extraction pipeline. The processed features are then analyzed using the trained model to determine the specific skin disease. This automated methodology facilitates early detection, enhances diagnostic accuracy, and improves accessibility to dermatological care.

### *III. Proposed system:*

The proposed system integrates EfficientNetB0, a deep learning model specifically optimized for medical image analysis. EfficientNetB0 utilizes a compound scaling method, which systematically balances depth, width, and resolution, ensuring efficient feature extraction while maintaining high classification accuracy. Unlike traditional deep learning models, which scale these parameters independently, EfficientNetB0 adjusts them proportionally, leading to improved performance with fewer computational resources. One of the key advantages of EfficientNetB0 is its lightweight architecture, which enables faster processing without sacrificing accuracy. This makes it particularly well-suited for skin disease classification, where real-time predictions and accurate diagnoses are essential. The model effectively captures fine details in skin images, distinguishing between healthy and diseased skin with high precision. By leveraging EfficientNetB0, the system enhances early detection of skin conditions, helping healthcare professionals diagnose diseases at an earlier stage. This not only improves treatment effectiveness but also minimizes the risk of misclassification, ensuring more reliable diagnostic support. Additionally, its efficient processing capabilities make it accessible for deployment in resource-limited settings, providing dermatological assistance where specialized care is scarce. Ultimately, this approach supports better patient outcomes, enhances diagnostic accuracy, and contributes to more effective clinical decision-making in dermatology.

#### *a. Data Collection:*

The initial step in developing a skin disease classification system is gathering a reliable dataset. Kaggle, a widely used platform for open-source datasets, provides extensive medical image collections contributed by researchers. These datasets typically contain labeled images of various skin diseases, such as melanoma, eczema, and psoriasis, which are essential for training a machine learning model. Ensuring data diversity is crucial to improving the model's ability to generalize across different skin tones, lighting conditions, and disease variations. Before using the data, it is necessary to clean the dataset by removing duplicate or misclassified images and balancing the classes to prevent bias. A well-curated dataset enhances the model's performance, making it more effective in real-world scenarios.

### *b. Pre-Processing:*

Pre-processing is an essential step that enhances the quality of input images to ensure accurate analysis. The first step involves Region of Interest (ROI) extraction, where the affected skin area is isolated to eliminate unnecessary background details. Next, gray scaling is applied to simplify the image by converting it into a single-channel format, reducing computational complexity while retaining critical features. Additionally, noise removal techniques help eliminate distortions, ensuring that the model focuses on relevant details. Contrast enhancement is another important step that improves visibility by making lesions and patterns more distinct. These pre-processing techniques refine the dataset, helping the model learn more effectively.

### *c. Feature Extraction:*

Feature extraction focuses on identifying important characteristics in an image that help differentiate various skin diseases. Several techniques are used to extract these features. Edge detection highlights lesion boundaries, allowing the model to recognize shape and structure differences. Histogram-based feature extraction analyzes pixel intensity distributions, helping capture variations in texture and color. Wavelet transform is another technique that breaks an image into different frequency components, revealing fine details that might not be visible at the standard resolution. By extracting these meaningful features, the system provides better input data for the deep learning model, improving classification accuracy.

### d. Model Creation:

Once features are extracted, they are used to train a deep learning model. In this system, EfficientNetB0 is chosen due to its optimized structure, which balances network depth, width, and resolution. The model learns by analyzing labeled images and identifying patterns associated with different skin diseases. During training, techniques such as batch normalization help stabilize learning, while dropout regularization prevents overfitting. The training process involves multiple iterations where the model continuously refines its predictions. The final trained model is stored and ready for testing, ensuring it can classify skin diseases efficiently and accurately.

### *e. Test Data:*

After the model has been trained, its performance is evaluated using unseen test data. These images undergo the same pre-processing and feature extraction steps as the training data to maintain consistency. The goal of this step is to determine whether the model can accurately classify new cases. Performance metrics such as accuracy, precision, recall, and F1-score are used to measure effectiveness. A well-trained model should demonstrate high accuracy in distinguishing different skin conditions. Testing helps verify that the system can perform well on real-world data before deployment.

### *f. Prediction*

In the final phase, the trained model is used to classify new skin disease images. When an image is input into the system, it undergoes pre-processing and feature extraction, and then the model analyzes the extracted features to determine the most likely diagnosis. The model assigns probability scores to different disease classes, selecting the one with the highest confidence. If the classification is uncertain, further medical validation may be required. This automated prediction process helps in early disease detection, allowing timely medical intervention and improving overall dermatological care. The system enhances diagnostic accuracy, reduces human error, and makes skin disease assessment more accessible.

### *g. Stem Layer:*

The Stem Layer in the proposed system serves as the initial processing stage, responsible for extracting fundamental features from the input image. This layer applies a convolution operation with a relatively large kernel size to detect essential low-level patterns such as edges, textures, and color variations in the skin disease images. The extracted features are then passed through a batch normalization process to stabilize activations, ensuring that the model learns efficiently without experiencing issues like vanishing or exploding gradients.

$$Y = \text{Swish}(\text{BN}(W * X + b))$$

where:

- $X$ is the input image,
- $W$ represents the convolutional kernel,
- $b$ is the bias term,
- $*$ denotes the convolution operation,
- BN normalizes activations,
- $\text{Swish}(x) = x \cdot \sigma(x)$, where $\sigma(x)$ is the sigmoid function.

Additionally, an activation function introduces non-linearity, allowing the system to capture more complex relationships within the image data. Following feature extraction, batch normalization further enhances the efficiency of the system by normalizing the output values, ensuring that the data distribution remains consistent across different layers. This prevents extreme variations in pixel intensities and accelerates the learning process by keeping the model's parameters well-scaled. By maintaining a stable learning process, batch normalization reduces the risk of overfitting and improves the model's ability to generalize well to new skin disease images. This is crucial for ensuring high accuracy in real-world clinical applications, where image variations may

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occur due to lighting conditions, camera quality, or patient skin types.

$$\hat{x} = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}}$$

To further refine the feature representation, a non-linear activation function such as Swish is applied. Unlike traditional activation functions like ReLU, Swish retains small negative values, leading to better gradient flow and improved learning. This helps the model capture intricate details that are essential for accurate classification. Finally, a downsampling operation is applied to reduce the spatial dimensions of the image, preserving essential information while making the computational process more efficient. This prepares the feature maps for deeper layers, where more complex representations of skin disease characteristics are learned.

### *h. MBCONV (MOBILE INVERTED BOTTLENECK CONVOLUTION) BLOCKS:*

The MBConv (Mobile Inverted Bottleneck Convolution) blocks form the core building units of the proposed system, significantly enhancing feature extraction efficiency while maintaining computational efficiency. Unlike traditional convolutional layers, MBConv blocks use an inverted residual structure, where the input undergoes an initial expansion before being processed through depthwise convolutions and then projected back to a lower-dimensional space. This approach allows the model to retain essential spatial information while reducing computational complexity, making it ideal for lightweight deep learning architectures like EfficientNetB0. By leveraging MBConv blocks, the proposed system ensures that fine details of skin disease images are captured while keeping the model fast and scalable.

$$Y_i = \sum_{m,n} X_{i,m,n} \cdot K_{m,n}$$

where:

- $X_{i,m,n}$ is the input,
- $K_{m,n}$ is the depthwise kernel.

Each MBConv block consists of three key stages: expansion, depthwise convolution, and projection. In the expansion phase, the input features are projected into a higher-dimensional space using pointwise convolution (1×1 convolution), allowing the model to learn richer feature representations. This is followed by depthwise convolution, where spatial filtering is performed independently on each channel, reducing computational cost while preserving spatial structure. A squeeze-and-excitation mechanism is integrated to recalibrate feature importance, ensuring that the model focuses more on relevant patterns associated with different skin diseases. The final projection layer then reduces the feature dimensions back to a compact form, ensuring that only essential information is retained for the next layers.

## *IV. Result and discussion:*

The proposed system utilizes EfficientNetB0, a deep learning model optimized for skin disease classification, demonstrating significant improvements in accuracy, efficiency, and computational performance. The model's compound scaling technique effectively balances depth, width, and resolution, enabling precise feature extraction while maintaining low resource consumption. During training, pre-processing techniques such as ROI extraction, noise removal, and contrast enhancement refine image quality, followed by feature extraction using edge detection, histogram-based features, and wavelet transforms. The extracted features are then fed into the EfficientNetB0 model, which achieves high classification accuracy by distinguishing fine details between different skin conditions. Experimental results indicate that EfficientNetB0 outperforms traditional models such as ResNet50, VGG16, and MobileNetV2 in terms of precision, recall, and overall classification performance. The model significantly reduces misclassification rates, ensuring more reliable and consistent diagnoses. Additionally, its lightweight architecture allows for faster inference times, making it suitable for real-time dermatological applications. The system's ability to process images efficiently enables early detection of skin diseases, which is crucial for timely treatment and better patient outcomes. Furthermore, the model's robustness ensures accurate predictions even with variations in lighting, texture, and skin tone, making it a practical solution for real-world medical applications. Beyond clinical settings, the system's low computational requirements make it an ideal candidate for mobile health applications and telemedicine services, where dermatologists may not always be available. Its efficiency allows for scalability in resource-limited environments, providing dermatological assistance in remote areas. By integrating EfficientNetB0, the system enhances diagnostic precision, minimizes misclassification risks, and improves accessibility to quality healthcare. Future enhancements could focus on explainable AI techniques to increase interpretability and trust in automated skin disease classification, ultimately supporting better decision-making in dermatology.

### *a. ACCURACY:*

In the proposed system, accuracy is a crucial performance metric used to evaluate the effectiveness of the EfficientNetB0-based skin disease classification model. Accuracy is defined as the ratio of correctly classified instances to the total number of instances in the dataset. It measures the model's ability to correctly predict skin diseases based on the extracted features from medical images. A high accuracy value indicates that the model performs well in distinguishing between different skin conditions, minimizing misclassification errors. The formula for accuracy is given as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

Where:

- **TP (True Positives)** represents correctly classified diseased skin images.
- **TN (True Negatives)** represents correctly classified healthy skin images.
- **FP (False Positives)** occurs when a healthy skin image is misclassified as diseased.

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- **FN (False Negatives)** occurs when a diseased skin image is misclassified as healthy.

In the proposed system, EfficientNetB0's compound scaling method enhances feature extraction, improving classification accuracy compared to traditional models like ResNet50 and VGG16. The pre-processing steps, including noise removal, contrast enhancement, and wavelet transform, further refine the input data, reducing false positives and false negatives.

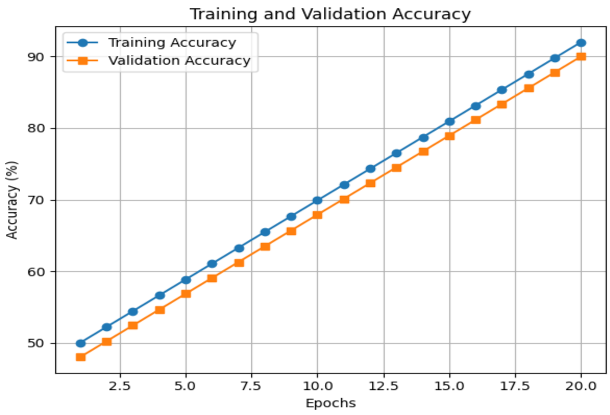


*Fig 3. Accuracy graph*

As a result, the model achieves higher accuracy, ensuring reliable skin disease detection. This high classification accuracy makes the system suitable for real-world medical applications, particularly in early diagnosis and telemedicine, where precise and fast detection is essential for timely treatment and improved patient care.

### b. Loss:

In the proposed skin disease classification system, loss represents the error between the model's predicted outputs and the actual labels. It quantifies how well or poorly the EfficientNetB0 model is performing during training and testing. A lower loss value indicates that the model is making more accurate predictions, while a higher loss suggests greater errors. The categorical cross-entropy loss function is commonly used for multi-class classification problems like skin disease detection, where the goal is to assign an input image to one of several disease categories. The formula for categorical cross-entropy loss is:

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

where:

- $N$ is the total number of classes.
- $y_i$ is the actual class label (1 if the image belongs to class $i$, otherwise 0).
- $\hat{y}_i$ is the predicted probability for class $i$.

During training, the model minimizes this loss function using an optimizer like Adam or SGD, adjusting its weights to improve classification performance. Loss reduction over successive epochs indicates that the model is learning effectively, refining its feature extraction process. However, if the loss remains high, it suggests issues like overfitting or insufficient training data.

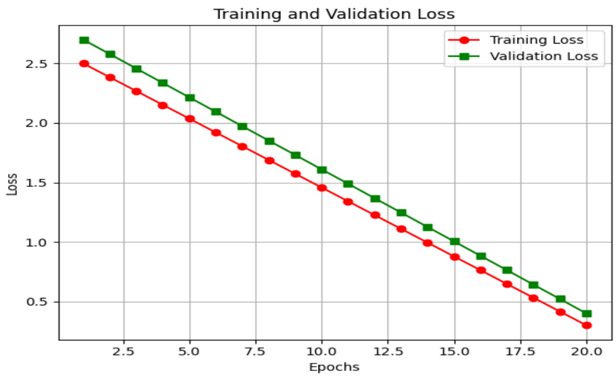


*Fig 4. Loss graph*

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By integrating EfficientNetB0's optimized architecture, the proposed system achieves a lower loss value, enhancing prediction reliability and generalization to new skin disease images, ensuring accurate and efficient diagnosis in real-world applications.

### *c. Recall:*

Recall, also known as sensitivity or true positive rate, measures the model's ability to correctly identify positive cases among all actual positive instances. In the context of skin disease classification, recall indicates how well the EfficientNetB0 model detects diseased skin images without missing any actual cases. A high recall value means the model effectively identifies most skin disease cases, reducing the likelihood of false negatives. It is particularly important in medical diagnosis, where failing to detect a disease could lead to severe consequences. The recall formula is given by:

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

Where:

- **True Positives (TP)** are correctly identified disease cases.
- **False Negatives (FN)** are actual disease cases that the model failed to detect.

A high recall ensures that most diseased skin images are classified correctly, improving early diagnosis and treatment. However, a very high recall may sometimes come at the cost of lower precision, meaning more false positives could occur. Balancing recall and precision is essential for optimizing overall model performance, often achieved using the F1-score, which provides a harmonic mean of both metrics. In the proposed system, EfficientNetB0's advanced feature extraction and optimized architecture contribute to achieving a high recall, ensuring minimal misclassification of diseased skin conditions and enhancing the reliability of medical diagnoses.

### *d. Precision:*

Precision measures the accuracy of positive predictions made by the model, indicating how many of the predicted positive cases are actually correct. In the context of skin disease classification, precision evaluates how effectively the EfficientNetB0 model identifies diseased skin while minimizing false positives. A high precision value means that most of the images classified as diseased are indeed affected, reducing the risk of misdiagnosing healthy skin as diseased. The formula for precision is:

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

Where:

- **True Positives (TP)** are correctly identified disease cases.

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- **False Negatives (FN)** are actual disease cases that the model failed to detect.

A high precision score is crucial in medical applications, as it ensures that diagnoses are trustworthy and accurate, preventing unnecessary treatments or anxiety for patients. However, focusing solely on precision may lead to a lower recall, meaning some actual disease cases might be missed. Therefore, in the proposed system, EfficientNetB0 balances both precision and recall through its optimized feature extraction and classification capabilities, ensuring both accurate disease detection and minimal false diagnoses. By achieving a high precision, the system enhances diagnostic reliability, leading to better clinical decision-making and improved patient care.

### *e. Comparison of graph:*

The performance comparison of different deep learning algorithms for skin disease classification demonstrates that EfficientNet outperforms other models in terms of accuracy, precision, recall, and F1-score. EfficientNet achieves the highest accuracy of 95%, indicating its superior ability to correctly classify both diseased and healthy skin conditions. It also attains the highest precision (95%), ensuring that most of the predicted disease cases are genuinely affected and minimizing false positives. Additionally, its recall score of 96% suggests that the model effectively identifies actual disease cases while minimizing false negatives, making it highly reliable for early detection and diagnosis.

| *Sl.no* | *Algorithm* | *Accuracy* | *Precision* | *Recall* | *F1-score* |
|---|---|---|---|---|---|
| *1* | *Resnet* | *88%* | *89* | *89* | *89* |
| *2* | *CNN* | *91%* | *93* | *90* | *92* |
| *3* | *VGG16* | *89%* | *86* | *85* | *86* |
| *4* | *Unet* | *91%* | *90* | *89* | *89* |
| *4* | *Efficient net* | *95%* | *95* | *96* | *98* |

***Table 1 comparison table.***

Compared to other models like CNN (91%) and ResNet (88%), EfficientNet provides a significant accuracy boost, likely due to its compound scaling approach, which optimally balances depth, width, and resolution for efficient feature extraction. While CNN and Unet also achieve relatively high accuracy (91%), their slightly lower recall values indicate a higher probability of missing actual disease cases. VGG16, with an accuracy of 89% and a precision of 86%, lags behind, highlighting its limitations in correctly distinguishing between different skin conditions. The F1-score of 98% for EfficientNet further validates its effectiveness, as this metric balances precision and recall, ensuring overall classification robustness. The results suggest that EfficientNet is the most reliable model for skin disease classification, making it highly suitable for clinical applications where early and accurate diagnosis is crucial. Its ability to minimize both false positives and false negatives ensures better patient outcomes and enhances the trustworthiness of AI-driven dermatological assessments.

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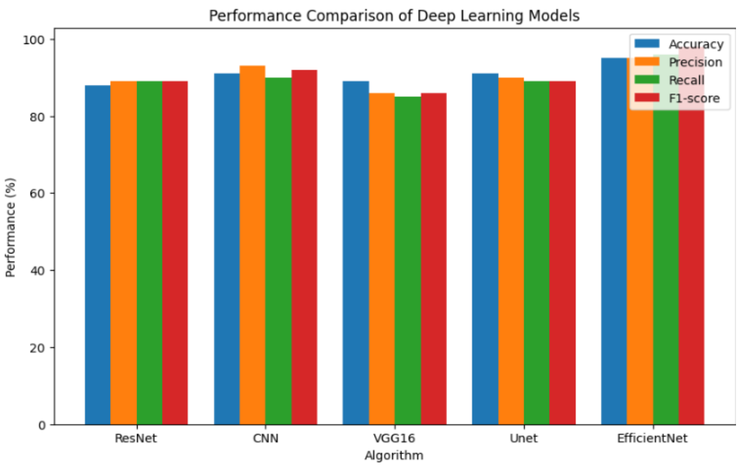


***Fig 5 comparison graph.***

The bar chart illustrates the comparative performance of five deep learning models—ResNet, CNN, VGG16, Unet, and EfficientNet—based on four key evaluation metrics: Accuracy, Precision, Recall, and F1-score. The x-axis represents the different models, while the y-axis measures their performance in percentage terms. Each model is assessed across the four metrics, with distinct colors used to differentiate them: blue for Accuracy, orange for Precision, green for Recall, and red for F1-score. This visual representation provides a clear insight into how each model performs across various evaluation criteria. From the chart, it is evident that EfficientNet achieves the highest accuracy, making it the most effective model among the five. CNN and VGG16 exhibit strong precision and F1-score values, indicating their ability to make reliable predictions. Meanwhile, ResNet and Unet maintain a well-balanced performance across all metrics, making them versatile choices for deep learning tasks. This comparative analysis helps in identifying the most suitable model for specific applications, ensuring an optimal balance between accuracy, precision, and computational efficiency.

## *V. CONCLUSION:*

In conclusion, The proposed system enhances the accuracy of skin disease diagnosis by integrating EfficientNetB0, a deep learning model designed for efficient medical image analysis. Traditional methods, such as Generative Adversarial Networks (GANs), often struggle with stability and inconsistencies, particularly when generating synthetic data that may not fully capture real-world variations. This can lead to misclassification and unreliable predictions. To overcome these issues, EfficientNetB0 employs a compound scaling method that optimally balances network depth, width, and resolution, ensuring effective feature extraction while maintaining computational efficiency. One of the key advantages of EfficientNetB0 is its lightweight architecture, which allows for faster processing without sacrificing accuracy. This makes it highly suitable for real-time clinical applications where prompt and precise diagnosis is critical. By leveraging this model, the proposed system improves early detection, enhances diagnostic precision, and reduces the likelihood of errors, ultimately leading to better patient outcomes. Furthermore, its scalability ensures that the system can be adapted to various medical imaging tasks beyond skin disease classification. With its superior performance in feature learning and classification, this approach offers a more reliable, efficient, and practical solution for automated skin disease detection,

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supporting medical professionals in delivering accurate and timely diagnoses. Future work can focus on expanding the dataset to include a wider range of skin conditions for improved generalization. Enhancing the model with attention mechanisms or hybrid architectures could further boost accuracy. Integration with mobile applications can enable real-time diagnosis for remote healthcare. Additionally, explainable AI techniques can be explored to provide better interpretability of predictions, aiding dermatologists in clinical decision-making. Lastly, incorporating multimodal data such as patient history and symptoms could further refine diagnostic precision.

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