Optimized Deep Learning Approach For Dermatological Condition Classification Using Efficient Net

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ABSTRACT:
Skin disorders are becoming more common, but because of the variety of conditions and the complexity of medical imaging, it is still difficult to provide an accurate diagnosis. Generative Adversarial Networks (GANs) are the mainstay of current systems for predicting skin diseases; yet, they suffer from instability and inconsistent training. Furthermore, when the generated images fall short of accurately capturing real-world variability, the dependence on artificial data production frequently leads to less accurate forecasts. The suggested approach uses EfficientNetB0, a deep learning model tailored for medical image processing, to get over these restrictions. EfficientNetB0 uses a hybrid scaling approach that equalizes depth, width, and resolutions, allowing for highly precise extraction of characteristics. It is perfect for classifying skin diseases because of its lightweight construction, which enables faster processing without sacrificing speed. Utilizing EfficientNetB0, the system lowers the risk of misclassification, increases early detection, and improves diagnostic accuracy—all of which contribute to improved 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

Accurate diagnosis is essential for the treatment of skin illnesses, which range from benign ailments to malignant malignancies. Long-term exposure to sunlight can induce actinic keratosis, a precursors skin condition that often appears in regions exposed to the sun as hard patches of scaling. Squamous cell carcinoma (SCC), A common type of carcinoma of the skin that affects the outer layers of the skin and usually manifests as red, scaly, or ulcerated patches, might develop if treatment is not received. In a similar vein, Basal cell carcinoma (BCC), a highly prevalent kind of carcinoma of the skin, usually manifests as whitish or waxy lumps. Early identification is crucial to preventing substantial tissue damage, even though BCC seldom spreads. Dermatofibroma is a solid, slow-growing nodule that is innocuous but may be mistaken for a malignant development. Melanoma, an aggressive type of skin cancer marked by dark, irregularly shaped lesions, can arise from nevus (mole), another frequent skin lesion composed of melanocytes. Furthermore, because of its dark pigmentation, pigmented benign keratosis, a non-cancerous skin disorder, might be mistaken for melanoma. Seborrheic keratosis is another skin condition that manifests as waxy, wart-like growths that can mimic malignant lesions even though they are benign. Hemangiomas and angiomas are examples of vascular lesions that arise from aberrant blood vessel growth and usually manifest as red or purplish skin markings. Because many illnesses share visual characteristics, sophisticated deep learning models such as EfficientNetB0 are essential for differentiating benign from malignant lesions, enhancing diagnostic precision, facilitating early diagnosis, and promoting improved patient care.

1) EfficientNetB0:

A The deep learning image classification model EfficientNetB0 is well-known for its excellent accuracy and computational efficiency, which makes it perfect for medical image analysis applications such as the diagnosis of skin diseases. By proportionally growing networks depth, width, and resolution, it employs a revolutionary compound scaling technique that maximizes performance without appreciably raising computing costs. The squeeze-and-excitation (SE) blocks in the model's architecture, which is based on mobile inverted bottleneck convolution (MBConv) layers, improve feature extraction and concentrate on the most pertinent data. EfficientNetB0 use depthwise separable convolutions, in contrast to conventional CNNs, to lower complexity without sacrificing accuracy. It is appropriate for real-time diagnostic tools and applications related to mobile health because to its lightweight and organized design, which enables speedier processing. EfficientNetB0 is particularly good at differentiating between seemingly identical situations, such benign and malignant skin lesions, thanks to its capacity to capture subtle details. This enhances early identification and evaluation in medical contexts.

Fig. 1 Architecture diagram of EfficientNetB0

2) Architecture diagram of proposed system:

The architectural framework illustrates a deep learning-driven method for categorizing skin conditions in two key stages: the training stage and the testing stage. Images of skin diseases are taken from Kaggle and treated using a variety of improvement techniques during the Training Phase, including as contrast adjustment, noise reduction, grayscale conversion, and Region of Interest (ROI) extraction, to guarantee image clarity. In order to highlight important patterns, feature extraction is then carried out utilizing edge detection, histogram-based features, and wavelet transform.

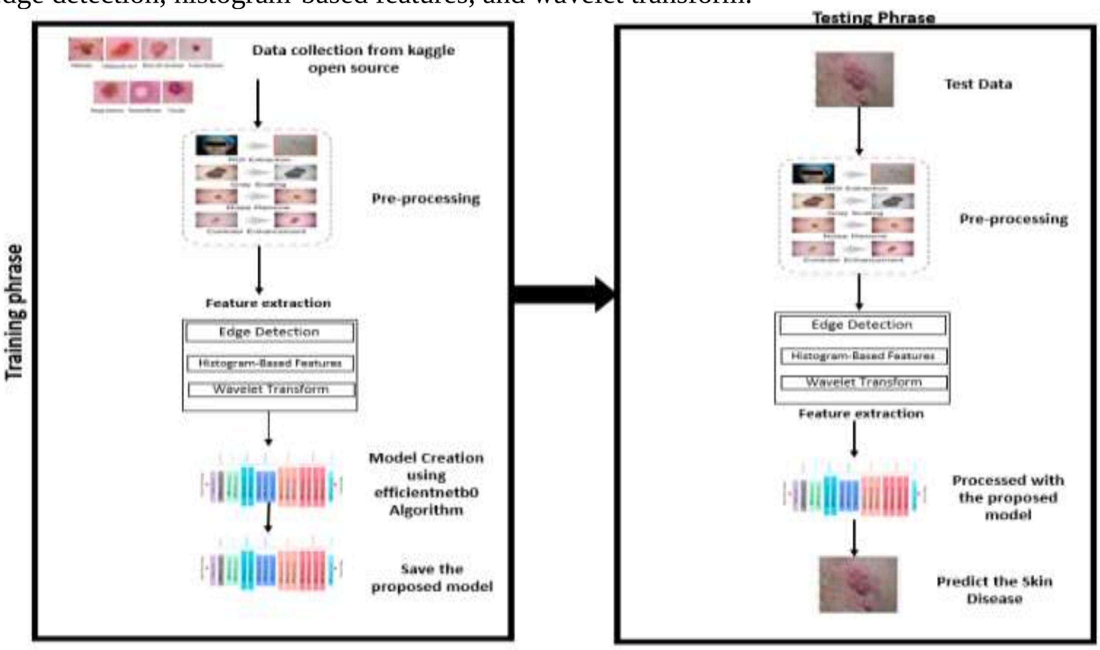

Fig. 2 Architecture diagram of proposed system

The EfficientNetB0 technique, which is tuned for accurate illness classification, is then applied to develop a model that uses deep learning using these enhanced features. For later use, the trained model is saved. The identical pre-processing and feature extraction workflow is applied to a fresh skin image during the Testing Phase. The trained model is then used to examine the processed characteristics and identify the particular skin condition. Early detection, improved diagnostic precision, and easier access to dermatological care are all made possible by this automated approach.

II. LITERATURE SURVEY

To develop m-Skin Doctor, a mobile-enabled application for initial melanoma dermatological cancer evaluation, Support Vector Machine (SVM) techniques have been used [2]. The approach improves diagnosis speed and accuracy by using SVM to categorize skin lesions and identify melanoma early. Accessibility is guaranteed by this mobile-based solution, which enables users to do exams in real time via their smartphones. The system offers a portable and effective tool for skin cancer screening by fusing machine learning with mobile technology, allowing people to keep an eye on the state of their skin without requiring for specialized medical equipment. This research examines the role of essential sample in the categorization of melanomas in images from dermoscopy using the bag-of-features (BoF) technique [3]. Important image attributes, which are regarded as "visual words," are captured using this method, and they are then analyzed for categorization using machine learning algorithms. The method showed that picking out important details from photos can greatly increase the bag-of-features method's accuracy, which helps with the earlier and more accurate identification of melanomas. Kuldeep Vayadande investigates the most recent Machine learning breakthroughs are transforming the diagnosis of skin diseases by increasing dermatology's precision, effectiveness, and accessibility. In addition to deep learning models like RNNs and GANs [6], techniques like KNN, SVM, and CNNs, as well as attention mechanisms, improve picture processing, automate diagnosis, and sharpen focus on afflicted areas. By offering reliable, impartial, and quick disease detection, these techniques get around the drawbacks of conventional inspection. In order to identify infected cells, detect viral infections, and examine transcriptional changes in human skin biopsies, a single-cell RNA sequencing technique [7] has been created. Merkel cell polyomavirus, HPV strains, and rubella virus transcripts were effectively identified using this technique, which was confirmed with 100% sensitivity and specificity. Additionally, it disclosed hitherto unidentified infected cell types and distinct viral-host interactions, including the emergence of the rubella virus E1 capsid protein exclusive to macrophages. The non-viral origins of non-viral inflammatory skin diseases were also confirmed by the absence of a continuous viral presence in these conditions. This method provides a potent tool for researching how viruses regulate genes in skin conditions. Using a Raspberry Pi, J.S. Leena Jasmine investigates the use of deep learning for identifying distinct dermatological disorders [8]. The study stresses how difficult it is for even seasoned doctors to diagnose skin disorders and how contemporary technology helps with prompt and precise identification. The system uses computational methods to process and categorize skin photos according to a number of criteria. Techniques for picture enhancement and noise reduction are used to increase diagnostic precision. A convolutional neural network (CNN) is used to identify the type of dermatological condition, and the outcomes are displayed on a Web of Things interface.

It is difficult to diagnose skin problems by visual inspection because of overlapping lesion characteristics, changes in skin texture, hair interference, and inadequate illumination. More sophisticated diagnostic frameworks are required because, despite improvements in lesion identification, computer vision (CV) and the capabilities of machine learning (ML) nevertheless remain restricted complicated artifacts. The suggested detection methodology uses a multi-step procedure to overcome these issues. Lesion segmentation is the first step in the process, which effectively uses Grey Wolf Optimization (GWO) and Optimized Region Growing (ORG) to distinguish between normal and unhealthy skin [9]. Next, features are extracted using the Weber Local Descriptor (WLD) for boundary details and the Gray Level Co-occurrence Matrix (GLCM) as textural patterns. After that, an autoencoder eliminates redundancy to improve these properties. Lastly, a Convolutional Neural Network (CNN) increases the precision of diagnosing skin diseases by classifying lesions based on extracted attributes. This study suggests an autoencoder-based classification algorithm and region-growing segmentation as an optimum way to overcome the challenges in identifying dermatological conditions [10]. The methodology's three primary steps are segmentation, extraction of characteristics, and categorization.The usage of fuzzy c-means grouping improves segmentation outcomes. Features are then extracted using the Local Binary Pattern (LBP) and Local Gabor XOR Pattern techniques. These characteristics are then handled by a hybrid classifiers that includes Convolutional Neural Networks (CNN) for geographic characteristic extraction and LSTM networks (Long Short-Term Memory) for sequential pattern identification. With 94.6% accuracy and 95.5% precision, this hybrid strategy outperforms the traditional FCM model in terms of prediction accuracy. Livestock are at risk from Lumpy Skin Disease (LSD), which calls for prompt and precise diagnosis to avoid financial losses. While an AI-based method employing using VGG16 [11] in Extreme Learning Machines (ELM) for obtaining features achieves 96.5% accuracy, traditional methods frequently lack efficiency. By successfully distinguishing between diseased and healthy livestock, our methodology guarantees prompt intervention and improved management. LeCun, Bengio, and Hinton (2015) gave a thorough account of the development of deep learning and its uses, highlighting how it has revolutionized a number of fields, including medical diagnosis. In dermatology, deep learning systems, specifically Convolutional Neural Networks (CNNs) [12]—have been extensively used to classify skin diseases, increasing the precision and effectiveness of diagnosis. Sinha, Sardana, and Saini (2014) [13] studied the prevalence of dermatological disorders among rural Indian medical facilities, highlighting the challenges in identifying and treating these conditions in underprivileged areas where a lack of dermatologists frequently results in delayed or inaccurate diagnoses. Furthermore, Agarwal, Satija, and Sengupta (2011)[14] discussed the more general problems of providing healthcare in rural India, highlighting the lack of enough infrastructure, the difficulty in obtaining high-quality medical care, and the requirement for scalable, reasonably priced solutions. By tackling the issue of vanishing gradients in deep networks, He et al. (2016) [15] presented deep residual learning, a method that greatly enhanced picture identification skills, especially in medical imaging. Together, this researchhighlight how crucial cutting-edge machine learning methods—like deep learning—are to enhancing the provision of healthcare, especially for dermatological disorders. With models like AlexNet laying the groundwork for medical imaging applications, Convolutional neural networks (CNNs) with deep learning [16] have completely changed picture categorization by dramatically increasing accuracy in large-scale datasets. Through the analysis of large datasets of tagged dermoscopic pictures, deep neural networks have been constructed in dermatology to efficiently discern between benign and malignant lesions and identify skin cancer with dermatologist-level accuracy. By choosing the most pertinent features, feature selection with dragonfly optimization [17] has improved psoriasis categorization even further, increasing accuracy while lowering computing complexity. The deep learning model for diagnosing chest radiographs, the CheXNeXt algorithm [19], showed expert-level performance in identifying several thoracic disorders, confirming AI's potential in medical imaging and its relevance to dermatology. Furthermore, to improve classification accuracy and resilience, a hybrid approach [20] for skin disease classification was presented by fusing output codes with deep convolutional error-correcting neural networks. These developments demonstrate how deep learning is revolutionizing medical diagnostics by enhancing early detection, lowering the need for specialized specialists, and guaranteeing more affordable healthcare options.

III. METHODOLOGY

1) Data Collection:

Collecting a trustworthy dataset is the first stage in creating a system for classifying skin diseases. Researchers have given large quantities of medical images to Kaggle, a popular site for open-source datasets. These datasets often contain tagged images of various dermatological conditions, including eczema, psoriasis, and melanoma, which are utilized for training a machine learning models. To increase the model's capacity to generalize across various skin tones, lighting situations, and illness changes, it is imperative to ensure data variety. To avoid bias, the dataset must be cleaned before use by eliminating duplicate or incorrectly categorized photos and balancing the classifications. The model performs better and is more useful in real-world situations when the dataset is carefully selected.

2) Pre-Processing:

To guarantee accurate analysis, one important step that raises the calibre of receiving images is pre-processing. In order to remove extraneous background information, the afflicted skin area is isolated in the first stage, known as Region of Interest (ROI) extraction. The image is then simplified via grey scaling, which reduces computing complexity while maintaining important details by transforming it into a single-channel format. Furthermore, by removing distortions, noise removal techniques make sure the model concentrates on essential details. Another crucial step that increases visibility is contrast enhancement, which makes patterns and lesions stand out. By improving the dataset, these pre-processing methods aid in the model's learning process.

3) Feature Extraction:

Finding key characteristics is the aim of separating features in an image that aid in the differentiation of different skin conditions. These features are extracted using a variety of methods. By highlighting lesion boundaries, edge detection enables the model to identify variations in shape and structure. By analyzing pixel intensity distributions, histogram-based feature extraction aids in capturing texture and color variations. Another method that separates an image into distinct frequency components and brings out fine details that might not be seen at ordinary resolution is the wavelet transform. Principal component analysis (PCA) may be used to lower the number of dimensions while preserving crucial information, improving computational efficiency. Furthermore, color space conversions, including changing RGB photos to LAB or HSV coloured areas, enhance color-based feature extraction, making it easier to distinguish between different skin conditions. The system improves the deep learning model's input data by extracting these significant characteristics, which raises the classification accuracy.

4) Model Creation:

The recovered characteristics are used for training a model that uses deep learning. EfficientNetB0 is chosen for this architecture due to its ideal topology, which balances networking depth, width, and resolution. By examining labeled photos and spotting patterns linked to various skin conditions, the model gains knowledge. While dropout regularization stops overfitting, batch normalization and other approaches help stabilize learning throughout training. The model continuously improves its predictions during the training process, which consists of several rounds. The finished trained model is saved and prepared for testing, guaranteeing its accurate and efficient classification of skin conditions.

5) Test Data:

After training, the model's effectiveness is evaluated using unlabeled data collected during tests, ensuring its ability to generalize beyond the training set. To maintain consistency, these images undergo the same pre-processing and feature extraction steps. This phase determines whether the model can accurately classify new cases. Effectiveness is measured using performance indicators like F1-score, recall, accuracy, and precision, which help evaluate its reliability. A well-trained model should not only distinguish between different skin diseases with high accuracy but also handle variations in lighting, texture, and image quality. Robust testing helps identify potential biases, overfitting, or misclassification issues, allowing for necessary refinements. Prior to deployment, thorough validation ensures the system performs effectively on real-world data, making AI-driven skin disease diagnosis more reliable and clinically applicable.

6) Prediction

In the final stage, new images of skin conditions are classified using the trained model. When an image is input into the system, it undergoes pre-processing to remove noise, normalize lighting, and enhance key features. These features are then extracted, and the model analyses them to predict the most likely diagnosis. The model assigns probability scores to various disease classes and selects the one with the highest confidence. If the classification results are unclear or ambiguous, additional medical validation or expert review might be necessary to ensure accuracy. This automated process accelerates early disease detection, enabling timely medical intervention. The use of AI technology significantly improves diagnostic accuracy by reducing human error and enhancing the evaluation of complex skin conditions. By continuously learning from new data and patient outcomes, the system can evolve, offering more precise and reliable diagnoses over time. Ultimately, this technology improves patient care and optimizes overall healthcare resource allocation.

7) Stem Layer:

As the first processing step in the suggested system, the Stem Layer is in charge of obtaining basic features from the input image. In order to identify crucial low-level patterns like edges, textures, and color variations in the skin disease images, this layer uses a convolution process with a comparatively high kernel size. As shown in Equation (1), the convolution operation extracts fundamental patterns, which are then passed through a batch normalization procedure to stabilize activations and ensure effective learning without encountering issues like vanishing or bursting gradients.

$$Y = \text{Swish}\,(BN\,(W * X + b)) \qquad (1)$$

WhereX is the picture that is input, W represents convolution kernel, b is the bias term, $*$ denotes convolution operation, BN normalizes activations, Swish(x) – x . σ(x), where σ(x) is the sigmoid function.

Furthermore, by adding non-linearity, an activation function enables the system to recognize more intricate associations in the visual data. After feature extraction, batch normalization, as described in Equation (2), ensures that the data distribution remains uniform across layers. This normalization process improves system performance by scaling output values effectively, preventing drastic changes in pixel intensities, and accelerating the learning process.

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

Where, x: The input feature (activation) from the convolutional layer, μ: The activation mean calculated across a mini-batch, σ^2: The activation variance calculated with the same mini-batch, ϵ: By adding a little constant to the denominator, division by zero is avoided, $\hat{x}$: The normalized output.

Batch normalization lowers the likelihood of overfitting and improves the model's ability to successfully generalize to new photos of skin diseases by preserving a steady learning process. This is essential for guaranteeing high accuracy in practical clinical applications, where factors like lighting, camera quality, and patient skin types may cause image differences. Additionally, the feature representation is further improved by applying a non-linear activation function, like Swish, as used in Equation (1). Swish maintains small negative values, improving gradient flow and learning in contrast to more conventional activation functions like ReLU. This helps the model capture minute details necessary for precise classification. In order to minimize the image's geographical dimensions while maintaining important information and increasing computational performance, a downsampling approach is finally used. This prepares the feature maps for deeper layers, where more intricate representations of skin disease characteristics are learned.

8) MBCONV (MOBILE INVERTED BOTTLENECK CONVOLUTION) BLOCKS:

The MBConv (Mobile Inverted Bottleneck Convolution) modules are the essential components of the proposed approach, which greatly improve feature extraction efficiency while preserving computing economy. The input goes through an initial expansion before being processed using depthwise convolutions and then projected back to a lower-dimensional space in MBConv blocks, which employ an inverted residual structure in contrast to conventional convolutional layers. This method is perfect for lightweight deep learning architectures like EfficientNetB0 because it reduces computational complexity while preserving crucial spatial information. In order to ensure that the model is rapid and scalable when collecting minute details of skin disorders images, the proposed method uses MBConv blocks.

$$Y_i = \sum_{m,n} X_{i,m,n} \,.\, K_{m,n} \qquad (3)$$

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

The three main steps of each MBConv block are projection, depth wise convolution, and expansion. The model can learn richer feature representations during the expansion phase by employing pointwise convolution (1×1 convolution) to project the input features onto a higher-dimensional space. Depth wise convolution comes next, which lowers computational costs while maintaining spatial structure by performing spatial filtering individually on each channel, as described in Equation (3). To rebalance feature importance and make sure the model concentrates more on pertinent patterns linked to various skin conditions, a squeeze-and-excitation mechanism is incorporated. In order to preserve just the most important information for the following layers, the final projection layer subsequently shrinks the feature dimensions back to a compact form.

IV. RESULT AND DISCUSSION

The proposed approach utilizes EfficientNetB0, a model developed using deep learning that has been optimized for dermatological condition category and exhibits significant improvements in computing economy, accuracy, and performance. The model's complex scalability approach skillfully balances depth, width, and resolution to extract features accurately while using little resources. Feature extraction employing edge detection, histogram-based features, and wavelet transforms comes after pre-processing methods including ROI extraction, noise reduction, and contrast enhancement improve image quality during training. The EfficientNetB0 model then uses the collected features to detect minute details between various skin states, achieving excellent classification accuracy. According to experimental data, the performance of EfficientNetB0 is superior on the basis of precision, recall, and total classification performance than more conventional models like ResNet50, VGG16, and MobileNetV2. By drastically lowering misclassification rates, the model guarantees more accurate and consistent diagnoses. Faster inference times are also made possible by its lightweight architecture, which qualifies it for real-time dermatological applications. Early detection of skin conditions is made possible by the system's effective image processing, which is essential for prompt treatment and improved patient outcomes. Beyond clinical settings, the system's minimal processing demands make it a great option for telemedicine services and mobile health applications, where dermatologists might not always be present. Its effectiveness enables scalability in settings with limited resources, offering dermatological support in isolated locations. The system increases accessibility to high-quality healthcare, reduces the risk of misdiagnosis, and improves diagnostic precision by integrating EfficientNetB0. Future developments might concentrate on explainable AI methods to improve automated skin disease classification's interpretability and credibility, which would ultimately aid in improved dermatological decision-making.

a. Accuracy:

Accuracy is a key performance indicator in the suggested system that is used to assess how well the EfficientNetB0-based skin disease classification model works. The proportion of correctly categorized cases to all instances in the dataset is known as accuracy. It assesses how well the model can use the features taken from medical photos to forecast skin conditions. A high accuracy rating means that the model minimizes misclassification mistakes by effectively differentiating between various skin states. The following is the accuracy formula:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100 \quad (4)$$

Where, TP (True Positives) provides accurately identified images of fatigued skin, TN (True Negatives) depicts accurately categorized images of healthy skin, FP (False Positives) occurs when a healthy skin image is misclassified as diseased, FN (False Negatives) occurs when a diseased skin image is misclassified as healthy.

Compared to traditional models like ResNet50 and VGG16, EfficientNetB0's compound scaling technique enhances feature extraction, thereby improving classification accuracy. Additionally, the pre-processing stages, including contrast enhancement and noise removal, refine the input data, further reducing misclassification errors. By leveraging the accuracy metric as defined in Equation (4), the proposed system ensures more reliable and precise skin disease diagnosis.

Fig.3 Accuracy graph

As depicted in Fig. 3 (Accuracy Graph), the model attains increased precision, guaranteeing dependable identification of skin conditions. Because of its high classification accuracy, as demonstrated in Equation (4), the system can be used in real-world medical applications, especially in telemedicine and early diagnosis, where prompt and accurate detection is crucial for better patient care and treatment.

b. Loss:

Loss is the term used to describe the disparity in the proposed dermatological condition classifying approach between the true labels and the expected outputs of the algorithm. It measures the effectiveness of the EfficientNetB0 model during testing and training. While a higher loss value implies more errors, a lower loss value shows that the model is producing more accurate predictions. The categorized cross-entropy function for loss is commonly used in multi-class classification problems, including skin disease finding, where the goal is to assign the image being processed to one of several illness categories. The categorical loss of cross-entropy calculation is:

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \quad (5)$$

Where, N is the total amount of classes overall, y_i is the true label (1 for images in class I, 0 otherwise), $\hat{y}_i$ is the estimated likelihood for class i. To enhance the accuracy of classification, the system makes use of an optimizer such as Adam or SGD to minimize this loss function during training. If the loss decreases over successive epochs,as demonstrated in Equation (5), it means that the model is learning well and improving its feature extraction process; if the loss stays high, it suggests problems such as overfitting or inadequate training data.

Fig.4 Loss graph

According to Figure 4 (Loss Graph), the suggested system achieves a lower loss value by incorporating the optimized architecture of EfficientNetB0, improving prediction reliability and generalization to new skin disease images, guaranteeing precise and effective diagnosis in practical applications.

c. Recall:

The model's recall, sometimes called true positive rate or sensitivities, it measures how successfully it can identify positive outcomes out from every actual positive cases. Recall, as it relates to skin disease classification, measures how well the EfficientNetB0 model identifies photos of diseased skin without overlooking any real cases. A high recall score lowers the possibility of false negatives by indicating that the model successfully detects the majority of skin disease cases. In medical diagnostics, when a disease's failure to be detected could have serious repercussions, it is especially crucial. The formula for recall is provided by:

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives(TP)} + \text{False Negatives(FN)}} \tag{6}$$

Where, True Positives (TP) are accurately recognized cases of illness, False Negatives (FN) are actual disease cases that the model failed to detect.

Early diagnosis and therapy are improved when a high recall, as defined in Equation (6), guarantees that the majority of photos of sick skin are correctly categorized. A very high recall, however, can occasionally come at the expense of decreased precision, which can cause the number of false positives to rise. Optimizing overall model performance requires striking a balance between recall and precision, The F1-score, which provides the harmonic average between the two measures, is often used to achieve this. The sophisticated feature extraction and optimized design of EfficientNetB0 let the suggested system achieve a high recall, as shown in Equation (6), guaranteeing little misclassification of skin diseases and boosting the accuracy of medical diagnoses.

d. Precision:

Precision quantifies the model's accuracy in predicting positive outcomes, showing the proportion of projected positive examples that turn out to be true. Precision measures how well the EfficientNetB0 model detects sick skin while reducing false positives in the context of skin disease classification. A high precision number lowers the possibility of misdiagnosing healthy skin as diseased because it indicates that the majority of the photos that are labeled as diseased are indeed impacted. The equation used for accuracy goes as outlined below:

$$\text{Precision} = \frac{\text{True Positives(TP)}}{\text{True Positives(TP)} + \text{False Positives(FP)}} \tag{7}$$

Where, True Positives (TP)are accurately recognized cases of illness, False Negatives (FN) are actual disease cases that the model failed to detect.

In medical applications, a high accuracy score, as defined in Equation (7), is essential since it guarantees reliable and precise diagnoses, avoiding needless treatments or patient concern. But concentrating only on accuracy could result in a reduced recall, which could mean that some real disease cases are overlooked. As a result, EfficientNetB0's optimized feature extraction and classification capabilities in the suggested system balance precision and recall, guaranteeing both precise disease identification and a low number of incorrect diagnoses. The method improves diagnostic reliability by reaching a high level of precision, which improves clinical judgment and patient care.

e. Comparison of graph:

When compared to other deep learning algorithms for the classification of skin diseases, EfficientNet outperforms various other models in terms of accuracy, precision, recall, and F1-score. With a 95% maximum accuracy, EfficientNet demonstrates its exceptional capacity to accurately diagnose both healthy and sick skin diseases. Additionally, it achieves the maximum precision (95%), reducing false positives and guaranteeing that the majority of anticipated disease cases are actually impacted. Additionally, its recall score of 96% implies that the model effectively identifies true disease cases while avoiding false negatives, making it extremely dependable 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

5	Efficient net	95%	95	96	98

Table 1: Performance Comparison of Deep Learning Models

EfficientNet offers a notable improvement in accuracy, as defined in Table 1, when compared to other models such as CNN (91%) and ResNet (88%). This is most likely due to its complicated sizing technique, which effectively extracts features by balancing depth, width, and resolution. Even though CNN and Unet both attain a respectable 91% accuracy rate, their little lower recall values suggest a greater likelihood of overlooking real disease cases. With an accuracy of 89% and a precision of 86%, VGG16 falls short, underscoring its shortcomings in accurately differentiating between various skin diseases. The efficacy of EfficientNet is further supported by its 98% F1-score, which ensures overall classification robustness by striking a balance among precision and recall. The outcomes show that EfficientNet is the most reliable model for skin disease classification, making it perfect for clinical scenarios where accurate and timely diagnosis is crucial. Its capacity for lowering false positives and false negatives guarantees improved patient outcomes and raises the credibility of dermatological evaluations powered by AI.

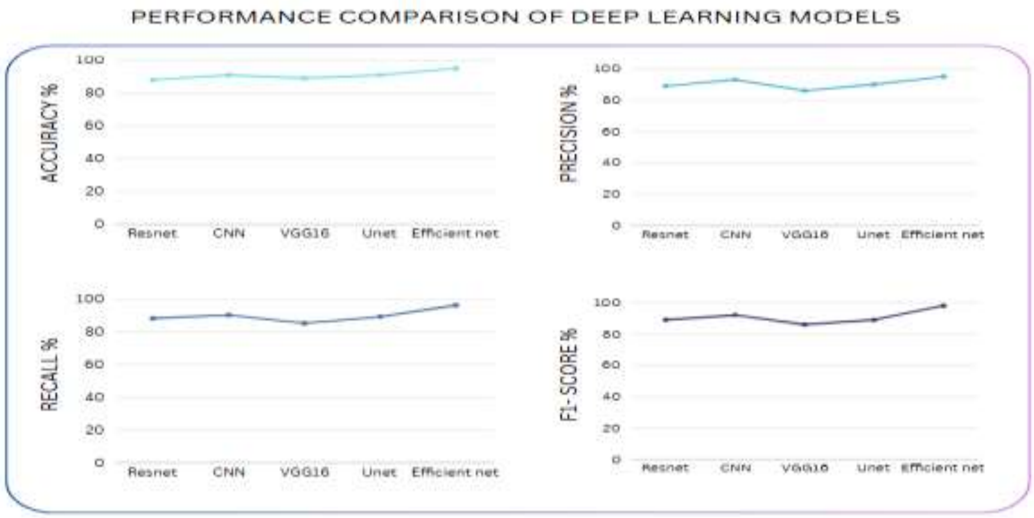

Fig. 5 Performance Comparison graph

Based on four important evaluation metrics—Accuracy, Precision, Recall, and F1-score—Fig. 5 evaluates and contrasts five deep learning models: CNN, VGG16, Unet, EfficientNet, and ResNet. The various models are represented on the x-axis, and their performance is expressed as a percentage on the y-axis. The four metrics are used to evaluate each model, and they are distinguished by different colors: red for F1-score, orange for precision, green for recall, and blue for accuracy. This graphic depiction offers a clear understanding of each model's performance in relation to several evaluation criteria. It is clear from the figure that EfficientNet is the most successful model out of the five since it attains the maximum accuracy. Strong precision and F1-score values, as depicted in Figure 5, demonstrate CNN and VGG16's capacity for accurate prediction. ResNet and Unet are flexible options for deep learning jobs since they consistently deliver well-balanced performance across all criteria. Through the establishment of optimal equilibrium between precision, accuracy, and computational efficiency, this comparison study aids in determining which model is best suited for particular applications.

V. CONCLUSION

The model is scalable for other medical imaging tasks, and it uses EfficientNetB0 to improve skin disease diagnosis with higher accuracy and faster processing. Prospective improvements include expanding datasets, using hybrid or attention-based models, integrating mobile apps, applying explainable AI, and combining data like symptoms and medical history for improved accuracy. Unlike unstable models like GANs, EfficientNetB0 ensures efficient feature extraction through balanced scaling, and its lightweight design makes it ideal for real-time clinical use, supporting early detection and reducing errors.

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