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AI-Based Skin Disease Detection and Treatment Recommendation: AI Dermacare

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ABSTRACT

Skin diseases are among the most common health issues worldwide, varying from mild conditions to severe chronic disorders that require timely diagnosis and treatment. Conventional skin disease prediction systems often utilize lightweight deep learning models such as MobileNet due to their efficiency and low computational requirements; however, these approaches may not achieve sufficient accuracy when handling complex and diverse dermatological datasets, leading to unreliable predictions in real-world applications. To address these limitations, the proposed system introduces HEPA-Net (H-E-P-A: Histogram Equalization, EfficientNetB0, Preprocessing, and Augmentation), a hybrid framework designed to enhance overall model performance. In this approach, histogram equalization improves image contrast, preprocessing ensures data consistency by removing noise and standardizing inputs, and augmentation increases dataset diversity to reduce overfitting, while EfficientNetB0 performs accurate feature extraction and classification. This integrated pipeline enables the system to capture fine-grained skin features more effectively, thereby improving classification accuracy while maintaining computational efficiency. The system further incorporates Explainable Artificial Intelligence (XAI) techniques to enhance transparency and user trust by generating visual explanations such as heatmaps, which assist users and healthcare professionals in understanding and validating predictions. Additionally, the system is designed to be user-friendly, allowing easy image input and quick interpretation of results, thereby supporting early detection and awareness of skin diseases. It also provides basic home remedy suggestions for minor conditions and recommends nearby dermatologists for further consultation, ensuring a complete healthcare support system. To ensure data privacy and security, patient information is encrypted and stored using the InterPlanetary File System (IPFS), providing a decentralized, secure, and tamper-resistant storage solution. Overall, the proposed system delivers an accurate, interpretable, secure, and user-centric solution for intelligent skin disease prediction and preliminary healthcare assistance.

Keywords: Skin Disease Prediction, EfficientNetB0, Explainable AI (XAI), IPFS, Deep Learning, Medical Image Analysis, Data Security.

I. Introduction:

Skin diseases are among the most common health problems worldwide, ranging from minor conditions to severe and life-threatening disorders that require timely diagnosis and treatment. Conditions such as actinic keratosis, basal cell carcinoma (BCC), and melanoma highlight the importance of early detection, as some lesions may progress into cancer if untreated, while benign conditions like dermatofibroma and seborrheic keratosis often resemble malignant ones, making accurate classification challenging. Traditional diagnosis relies on visual examination by dermatologists, which can be subjective, time-consuming, and prone to errors, especially in areas with limited medical access. With advancements in Artificial Intelligence (AI) and Deep Learning (DL), automated skin disease detection systems have improved diagnostic accuracy; however, conventional models such as CNNs and MobileNet often struggle with complex datasets. To overcome these limitations, the proposed system utilizes HEPA-Net, a hybrid framework integrating Histogram Equalization, Preprocessing, Augmentation, and EfficientNetB0**,** to enhance feature extraction and improve classification performance. The system also incorporates Explainable Artificial Intelligence (XAI) for transparent predictions, provides basic home remedy suggestions, and recommends nearby dermatologists. Additionally, patient data is securely stored using the InterPlanetary File System (IPFS), ensuring privacy and protection. Overall, the system offers an accurate, interpretable, and user-friendly solution for skin disease detection and early healthcare support.

a. HEPA-NET Algorithm:

Figure 1.1 HEPA-Net Architecture Diagram

HEPA-Net is a hybrid framework proposed for efficient and accurate skin disease classification, integrating four key stages: Histogram Equalization (H), EfficientNetB0 (E), Preprocessing (P), and Augmentation (A)**.** Unlike traditional standalone deep learning models, HEPA-Net combines image enhancement, data preparation, and classification into a unified pipeline to improve overall performance. Histogram Equalization enhances image contrast and highlights important features such as lesions and textures, while preprocessing ensures data consistency through resizing, normalization, and noise removal. Augmentation increases dataset diversity using transformations like rotation, flipping, and scaling, reducing overfitting and improving generalization. Finally, EfficientNetB0 serves as the core model for feature extraction and classification, leveraging its optimized architecture for high accuracy with low computational cost. This integrated approach enables effective extraction of fine-grained features and improves the system's ability to distinguish between visually similar skin diseases, resulting in enhanced accuracy, robustness, and reliability for real-world applications. The overall workflow of the proposed HEPA-Net framework is illustrated in Fig. 1.1.

b. Explainable Artificial Intelligence (XAI):

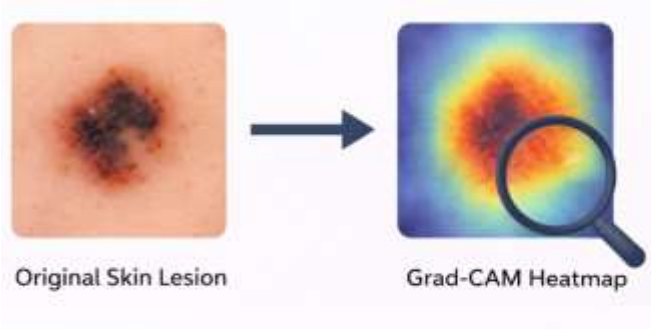

Figure 1.2 XAI Visualization of Skin Disease Prediction

Explainable Artificial Intelligence (XAI) plays a crucial role in improving the transparency and interpretability of deep learning models, especially in healthcare applications such as skin disease detection. Traditional deep learning models often function as black boxes, making it difficult to understand how predictions are made, which can reduce trust among users and medical professionals. To address this issue, the proposed system integrates XAI techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) to generate visual explanations in the form of heatmaps. These heatmaps highlight the important regions of the skin image that contribute most to the model's prediction, allowing users and dermatologists to verify whether the system is focusing on the correct lesion areas. The visual explanation generated by the model is illustrated in Fig. 1.2. This improves confidence in the model's decisions and supports better clinical validation. By enhancing interpretability and accountability, XAI ensures that the system is not only accurate but also reliable and trustworthy for real-world medical applications.

c. IPFS (Data Security):

The InterPlanetary File System (IPFS) is a decentralized storage technology used in the proposed system to ensure secure and reliable handling of patient data. Unlike traditional centralized storage systems, IPFS distributes data across a network of nodes, reducing the risk of single-point failures and unauthorized access. In this system, patient information and medical records are encrypted before being stored on IPFS, ensuring confidentiality and protection against data breaches. Each file is assigned a unique cryptographic hash, which guarantees data integrity and prevents tampering. This decentralized and tamper-resistant approach enhances patient privacy and ensures that sensitive medical information remains secure while still being accessible when needed. By integrating IPFS, the system provides a robust and trustworthy solution for managing healthcare data in skin disease detection applications.

II. Literature survey:

[1] Kuldeep Vayadande, Amol A. Bhosle, and Rajendra G. Pawar:

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 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, and Sk Hasane Ahammad:

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 et al.:

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] Dasari Anantha Reddy et al.:

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. 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 refines features by removing redundancy, and a CNN then classifies lesions, improving diagnostic accuracy.

[5] Kuldeep Vayadande, Om Lohade, Sumit Umbare:

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 et al.:

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.

[7] Mostafiz Ahammed et al.:

Skin diseases are widespread health concerns that not only affect physical well-being but can also lead to psychological distress and, in severe cases, skin cancer. Accurate diagnosis from clinical images is challenging due to the visual similarity between different skin conditions and the subjective, time-consuming nature of manual examination by dermatologists. To address these issues, this work proposes an automated skin disease prediction framework that improves diagnostic efficiency and reliability. The approach begins with digital hair removal using morphological filtering techniques such as Black-Hat transformation and inpainting, followed by Gaussian filtering to reduce noise and blur. Automatic GrabCut segmentation is then applied to isolate the affected lesion regions. For feature extraction, Gray Level Co-occurrence Matrix (GLCM) and statistical features are used to capture texture and intensity patterns from skin images. These features are classified using Decision Tree, Support Vector Machine, and K-Nearest Neighbor algorithms to identify eight types of skin diseases. Experiments on ISIC 2019 and HAM10000 datasets show that SVM achieves the best performance, demonstrating the effectiveness of the proposed method.

[8] Sadia Ghani Malik et al.:

Dermatological conditions are common in humans and are influenced by environmental, climatic, and biological factors, making timely diagnosis essential to prevent minor issues from progressing into severe diseases. However, accurate skin disease diagnosis remains challenging for healthcare professionals due to the reliance on visual inspection, which can be subjective and time-consuming. To overcome these limitations, this paper presents a Computer Assisted Diagnosis (CAD) framework that leverages data-driven techniques for early detection of skin diseases. A lightweight and computationally efficient Convolutional Neural Network (CNN) model is proposed and evaluated against both shallow and deep learning models. The designed CNN, consisting of seven convolutional layers, achieves an accuracy of 87.64% across three disease categories. Experiments conducted on the ISIC dermoscopic image dataset demonstrate the effectiveness of the proposed approach, highlighting its potential for accurate, efficient, and scalable automated skin disease diagnosis.

[9] G. Gayathri et al.:

Skin diseases are a major global health concern, affecting people of all age groups. Traditional diagnosis relies on dermatologists' visual examination, which can be time-consuming, subjective, and prone to errors, especially in areas with limited access to specialists. To address these challenges, this study presents an automated skin disease prediction system using the VGG16 deep learning model. The system incorporates preprocessing techniques such as image resizing, normalization, and data augmentation to improve performance. By leveraging transfer learning, VGG16 effectively extracts features and enables accurate classification. The system is designed for deployment on web and mobile platforms, providing real-time diagnosis, improving accessibility, and supporting better healthcare outcomes.

2.1 Comparison Table

[10] V. Auxilia Osvin Nancy et al.:

Skin is a vital and complex organ of the human body, and increasing exposure to harmful elements such as nitrates, arsenic, ultraviolet (UV) rays, and excessive sunlight—driven by pollution and ozone layer depletion—has led to a rapid rise in skin diseases. Automatic skin disease recognition remains challenging due to low contrast, high visual similarity among lesions, and large variations in color, shape, size, and illumination. Early detection, especially of skin cancer, is critical for reducing mortality. Artificial Intelligence (AI) and Machine Learning (ML) technologies play a key role in supporting physicians by enhancing diagnostic accuracy and minimizing human error. In several studies, ML and deep learning (DL) models have matched or even outperformed professional dermatologists. Pre-trained architectures such as ResNet152, AlexNet, and VGGNet are widely used for feature extraction, classification, and lesion segmentation. Public datasets like ISIC 2019 and HAM10000 are commonly employed. This study reviews technical research from 2018 to October 2022, highlighting trends and improved accuracy achieved by integrating clinical data with deep learning models. However, the study also identifies limitations such as high computational complexity, lack of model interpretability, and challenges in handling diverse real-world data, indicating the need for more efficient and explainable frameworks for practical deployment.

Table 2.1 Comparison with the Existing System

Sl. No	Author(s)	Year	Title	Concept	Drawback	Description
1	Kuldeep Vayadande, Amol A. Bhosle, Rajendra G. Pawar	2024	Innovative Approaches for Skin Disease Identification in Machine Learning	ML & CNN-based skin disease classification	Limited discussion on real-time deployment	Explores traditional ML (KNN, SVM) and CNNs for skin disease detection, highlighting AI's role in improving diagnostic accuracy and consistency.
2	Syed Inthiyaz, Baraa Riyadh Altahan, Sk Hasane Ahammad	2022	Skin Disease Detection Using Deep Learning	CNN, RNN, and ML models	Sequential models increase computational cost	Evaluates CNN, RNN, SVM, and Random Forest models; RNN achieves 92% accuracy, especially effective for tumor detection.
3	Syed Inthiyaz, Baraa Riyadh Altahan, Sk Hasane Ahammad	2023	Deep Learning in Skin Disease Image Recognition	Systematic review & model fusion	Depends heavily on dataset quality	Reviews 45 studies since 2016, showing that multi-model fusion outperforms traditional and single DL models.
4	Dasari Anantha Reddy, Swarup Roy, Sanjay Kumar,	2023	Optimized Region Growing and Autoencoder-Based Classification	ORG + GWO segmentation with CNN	Complex multi-stage pipeline	Uses optimized segmentation, texture features (GLCM, WLD), autoencoder compression, and CNN for improved lesion classification.

	Rakesh Tripathi					
5	Kuldeep Vayadande, Om Lohade, Sumit Umbare	2024	Automated Multiclass Skin Disease Diagnosis Using Deep Learning	Multiclass DL classification	Requires large labeled datasets	Proposes a deep learning model for early detection of multiple skin diseases, improving access in underserved regions.
6	Mostafiz Ahammed, Md. Al Mamun, Mohammad Shorif Uddin	2022	ML-Based Skin Disease Detection Using Image Segmentation	ML with preprocessing & segmentation	Limited scalability for complex cases	Employs hair removal, GrabCut segmentation, GLCM features, and ML classifiers; SVM performs best on ISIC & HAM10000 datasets.
7	Mohammad Shorif Uddin et al.	2024	High-Precision Skin Disease Diagnosis through DL	Lightweight CNN (7 layers)	Moderate accuracy compared to deeper models	Proposes a CAD system achieving 87.64% accuracy on ISIC dermoscopic images with computational efficiency.
8	G. Gayathri et al.	2025	Skin Disease Prediction Using Deep Learning	Transfer learning with VGG16	High dependency on pretrained weights	Uses VGG16 with preprocessing and augmentation for real-time web/mobile-based skin disease diagnosis.
9	V. Auxilia Osvin Nancy et al.	2025	Role of AI and DL in Skin Disease Prediction	Systematic review & meta-analysis	No experimental validation	Reviews DL models (ResNet, VGG, AlexNet) and datasets, highlighting improved accuracy via clinical data integration.
10	Somil Gambhir, Sanya Khanna, Priyanka Malhotra	2025	ML-Based Diagnosis of Lumpy Skin Disease	Climate-based ML prediction	Focused only on cattle disease	Uses geospatial and climatic data with ML models; Decision Tree shows strong performance for disease monitoring and vaccination planning.

2.2 Proposed System Architecture:

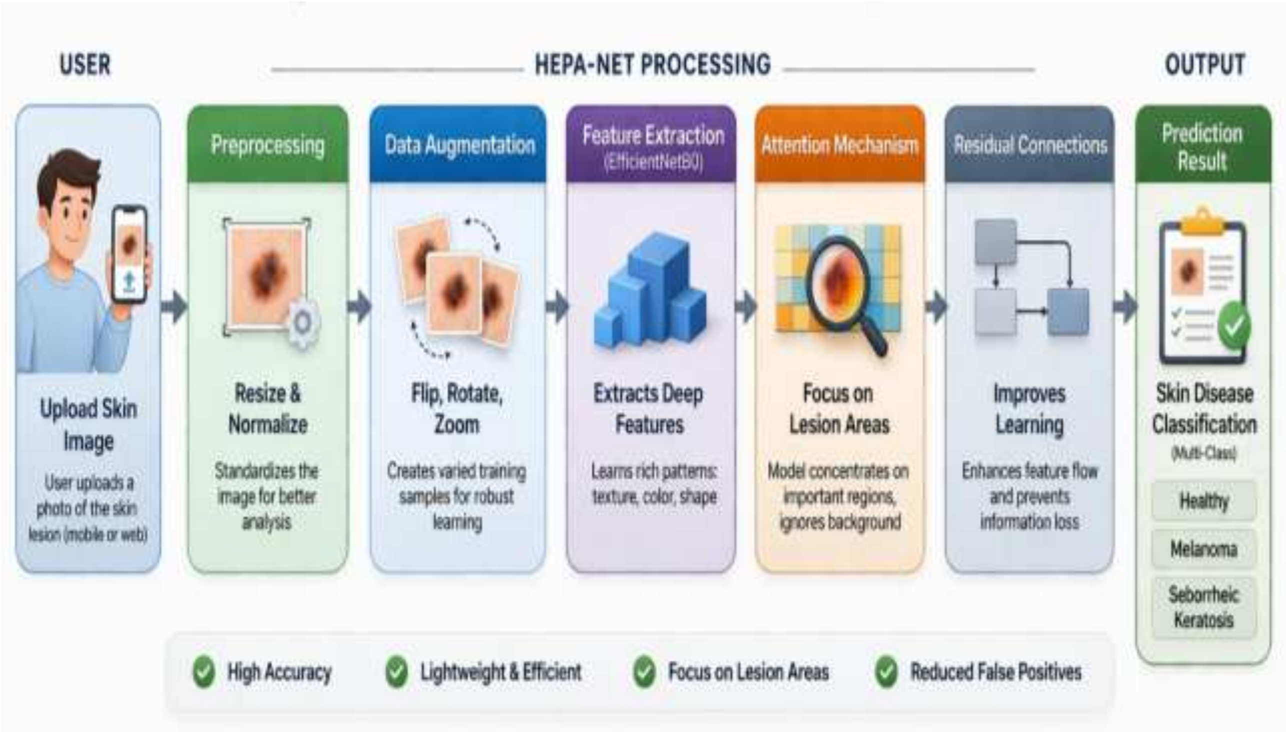

Figure 2.1 Skin Disease Prediction System Architecture using HEPA-NET

The overall architecture of the proposed system is illustrated in Fig. 2.1. The system is based on the HEPA-Net framework, which follows a structured pipeline for accurate skin disease classification. Initially, the input skin image is provided to the system, where Histogram Equalization (H) is applied to enhance image contrast and highlight important features such as lesions and textures. The enhanced image then undergoes Preprocessing (P), which includes resizing, normalization, and noise removal to ensure consistent and high-quality input data.Next, Augmentation (A) techniques such as rotation, flipping, and scaling are applied to increase dataset diversity and improve model generalization, reducing overfitting. The processed data is then passed to EfficientNetB0 (E), which acts as the core classification model. EfficientNetB0 extracts deep features from the images and performs accurate classification of different skin diseases. After classification, the system integrates an Explainable Artificial Intelligence (XAI) module to generate heatmaps using Grad-CAM, helping users understand the prediction. Additionally, patient data is securely stored using IPFS, ensuring privacy through encryption and decentralized storage. This integrated architecture improves accuracy, interpretability, and security compared to traditional approaches.

III. Proposed System:

The proposed HEPA-Net-based skin disease detection system is designed to provide an accurate and efficient method for identifying various skin diseases from images. The system integrates multiple stages including Histogram Equalization, Preprocessing, Augmentation, and classification using EfficientNetB0, along with Explainable Artificial Intelligence (XAI) and secure data storage. Unlike traditional approaches, the HEPA-Net framework focuses on improving feature quality, enhancing dataset diversity, and achieving better classification performance with reduced computational complexity. The overall system consists of modules such as data collection, image enhancement, classification, prediction, explanation, and secure storage.

3.1 Data Collection:

Data collection is a crucial step in building a robust skin disease detection system. In this work, skin disease images are collected from publicly available datasets such as ISIC, HAM10000, and Kaggle repositories, which contain a wide variety of dermatological conditions. These datasets include images of diseases such as melanoma, acne, eczema, psoriasis, and other skin lesions. Each image is labeled according to its respective disease class to support supervised learning.

To ensure data quality, preprocessing steps such as removal of duplicate images, elimination of blurred samples, and filtering of low-resolution images are performed. The dataset is carefully balanced to prevent bias toward specific classes. The final dataset is divided into training, validation, and testing sets, enabling effective model training, parameter tuning, and performance evaluation.

3.2 Histogram Equalization (H):

Histogram Equalization is applied as an initial image enhancement technique to improve contrast and visibility of skin lesion features. Many skin images suffer from poor lighting conditions and low contrast, which can obscure important patterns. This technique redistributes pixel intensity values to enhance the overall contrast of the image.

By highlighting key features such as lesion boundaries, texture variations, and color differences, histogram equalization helps the model focus on relevant regions. This step plays a significant role in improving feature extraction and contributes to better classification accuracy.

3.3 Image Preprocessing (P):

Image preprocessing is performed to standardize the dataset and improve input quality. All images are resized to a fixed resolution to ensure uniformity across the dataset. Normalization is applied to scale pixel values within a specific range, which helps in stabilizing the training process.

Additionally, noise removal techniques are used to eliminate unwanted artifacts that may affect model performance. Background variations are minimized to focus on the lesion area. These preprocessing steps ensure that the input data is clean, consistent, and suitable for deep learning models.

3.4 Data Augmentation (A):

Data augmentation is used to artificially increase the size and diversity of the dataset. This is particularly important in medical imaging, where obtaining large labeled datasets can be challenging. Techniques such as rotation, flipping, scaling, and translation are applied to generate new variations of existing images.

Augmentation helps the model learn invariant features and improves its ability to generalize to unseen data. It also reduces overfitting by preventing the model from memorizing training samples. As a result, the model becomes more robust and performs better in real-world scenarios.

3.5 Classification using EfficientNetB0 (E):

EfficientNetB0 serves as the core classification model in the HEPA-Net framework. It is a state-of-the-art deep learning architecture that uses a compound scaling method to balance network depth, width, and resolution. This allows the model to achieve high accuracy with fewer parameters compared to traditional CNNs.

The model utilizes transfer learning, where pre-trained weights are fine-tuned on the skin disease dataset. EfficientNetB0 effectively extracts complex features such as texture patterns, color variations, and lesion shapes. Fully connected layers are added for final classification into multiple disease categories. This approach ensures high performance while maintaining computational efficiency.

3.6 Test Data Evaluation:

After training, the model is evaluated using unseen test data to assess its generalization capability. The test images undergo the same preprocessing and augmentation pipeline before being fed into the model. Performance metrics such as accuracy, precision, recall, and F1-score are calculated to evaluate the effectiveness of the system.

These metrics provide a comprehensive understanding of model performance, including its ability to correctly classify diseases and minimize errors. A high evaluation score indicates that the model performs reliably and is suitable for practical deployment.

3.7 Disease Prediction:

In the prediction phase, the trained HEPA-Net model is used to classify new input images. The uploaded skin image is processed through all stages of the pipeline, including enhancement and normalization. The model then predicts the disease category based on learned features.

The system generates probability scores for each class and selects the class with the highest probability as the final prediction. The output is displayed along with confidence values, enabling users to understand the reliability of the prediction. This module provides quick and efficient preliminary diagnosis.

3.8 Patient Data Storage using IPFS:

To ensure data security and privacy, the system incorporates the InterPlanetary File System (IPFS) for storing patient data and prediction results. Before storage, the data is encrypted to prevent unauthorized access. IPFS provides a decentralized and tamper-resistant storage mechanism, ensuring data integrity and confidentiality.

This approach eliminates dependency on centralized servers and enhances security against data breaches. By combining encryption with decentralized storage, the system ensures that sensitive patient information is protected, making it suitable for real-world healthcare applications.

3.9 HeapNet Stem Layer

The HeapNet Stem Layer is the initial stage of the proposed HeapNet architecture. It extracts low-level features such as edges, textures, and color variations from input skin images. This layer applies convolution, batch normalization, and activation function to improve feature representation and stabilize training.

The mathematical representation of the HeapNet stem layer is given in Equation (1):

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

Where

- X = Input Image
- W = Convolution Weights
- b = Bias
- BN = Batch Normalization
- Y = Output Feature Map

This layer improves feature extraction and prepares the image for deeper HeapNet layers.

3.10 HEPA-Net MBConv Feature Learning Blocks

The HEPA-Net model uses MBConv blocks to improve feature learning while reducing computational complexity. The MBConv block consists of an expansion layer, depthwise convolution, and a projection layer.

The Depthwise Convolution operation is defined in Equation (2):

$$Y = \sum(m,n)\ X(i+m, j+n) \cdot K(m,n) \quad (2)$$

Where:

- X = Input Feature Map
- K = Convolution Kernel
- Y = Output Feature Map

The Expansion Layer is given in Equation (3):

$$F\_exp = \text{Conv}1\times1\ (X) \quad (3)$$

The Depthwise Convolution si given in Equation (4):

$$F\_dw = \text{Conv\_dw}\ (F\_exp) \quad (4)$$

The Projection Layer is defined in Equation (5):

$$F\_out = \text{Conv}1\times1\ (F\_dw) \quad (5)$$

The HEPA-Net MBConv blocks improve model accuracy, reduce computation, and enable efficient skin disease classification.

IV. Results and Discussion:

The performance of the proposed HEPA-Net framework is evaluated using standard metrics such as accuracy, loss, precision, recall, and F1-score. The results show that the model outperforms traditional approaches due to its integrated preprocessing and classification pipeline. Techniques such as histogram equalization, preprocessing, and data augmentation improve image quality and dataset diversity, while EfficientNetB0 enhances feature extraction and classification. These improvements lead to better generalization and more reliable performance, ensuring accurate and efficient skin disease detection.

4.1 Accuracy:

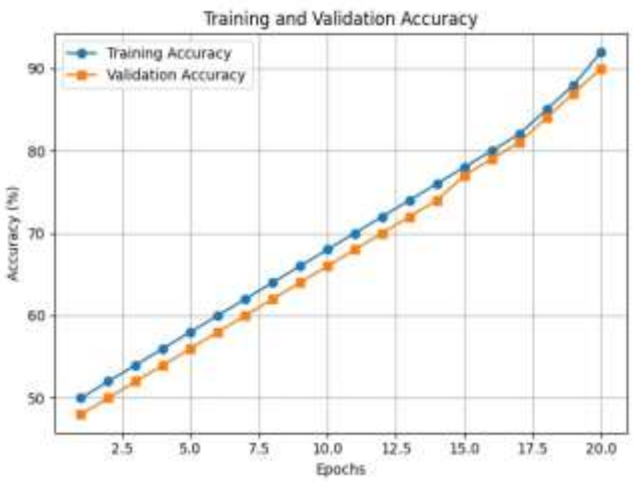

Figure 4.1: Training and Validation Accuracy

Accuracy measures the overall correctness of the model in classifying skin diseases, as illustrated in Fig. 4.1 and defined in Equation (6).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \qquad (6)$$

The proposed HEPA-Net model achieves an accuracy of 96%, outperforming traditional models such as CNN, ResNet, VGG16, and UNet. This improvement is due to enhanced feature extraction using preprocessing and EfficientNetB0.

4.2 Loss:

The loss function measures the difference between predicted and actual values. The model uses categorical cross-entropy loss, as defined in Equation (7).

$$Loss = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \qquad (7)$$

Where:

- N= Number of classes
- y_i= Actual label
- $\hat{y}_i$= Predicted label

The HEPA-Net model shows faster convergence and lower loss during training, indicating efficient learning.

4.3 Recall:

Recall measures the model's ability to correctly identify actual positive cases, as defined in Equation (8).

$$Recall = \frac{TP}{TP+FN} \qquad (8)$$

The proposed system achieves a recall of **96%**, ensuring that most disease cases are correctly detected. This is especially important for early diagnosis of critical conditions.

4.4 Precision:

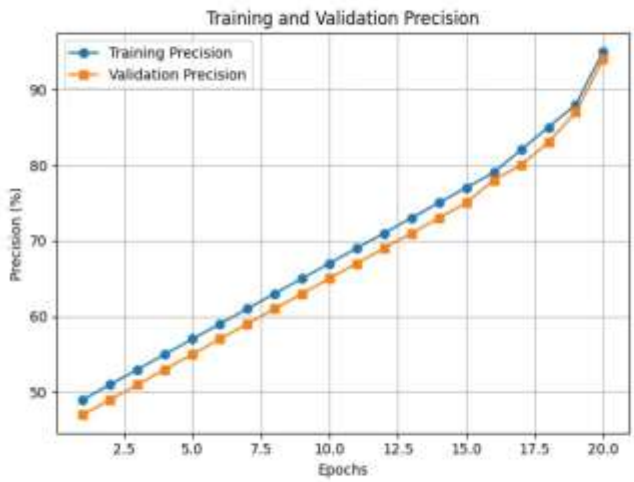

Figure 4.2: Training and Validation Precision

Precision measures the reliability of predictions. It shows how many predicted positives are correct, as illustrated in Fig. 4.2 and defined in Equation (9).

$$Precision = \frac{TP}{TP+FP} \qquad (9)$$

The HEPA-Net model achieves 95% precision, reducing false positives and improving diagnostic accuracy.

4.5 F1-Score:

F1-score provides a balance between precision and recall, as defined in Equation (10).

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (10)$$

The model achieves a high F1-score of 95%, indicating strong overall performance.

4.6 Comparison of Deep Learning Models:

This section presents a comparative analysis of the proposed HEPA-Net model with existing deep learning models. The performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The comparison helps to demonstrate the effectiveness and superiority of the proposed approach in handling skin disease classification tasks.

Table 4.1 Comparison of Deep Learning Models

Sl No.	Algorithm	Accuracy	Precision	Recall	F1 Score
1	ResNet	88%	89%	89%	89%
2	CNN	91%	92%	93%	92%
3	VGG16	89%	86%	85%	86%
4	UNet	90%	90%	89%	89%
5	**HEPA-Net**	**96%**	**95%**	**96%**	**95%**

The results clearly show that HEPA-Net outperforms all existing models due to its integrated pipeline and efficient feature extraction.

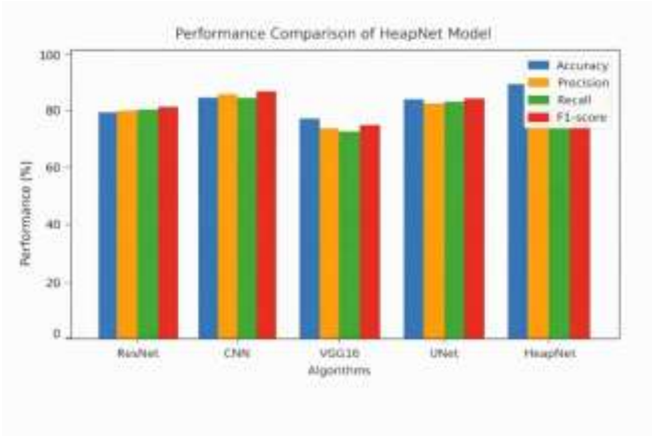

Figure 4.1 Performance Comparison of HEPA-Net with Existing Models

Fig. 4.1 shows the performance comparison of the proposed HEPA-Net model with existing models such as ResNet, CNN, VGG16, and U-Net. The graph illustrates evaluation metrics including accuracy, precision, recall, and F1-score for each model. It can be observed that HEPA-Net consistently achieves higher values across all metrics, demonstrating its superior classification capability. This improvement is achieved through the integration of histogram equalization, preprocessing, augmentation, and EfficientNetB0, which enhances feature extraction and model generalization. In contrast, traditional models show comparatively lower performance due to limitations in handling complex and diverse skin disease datasets. Therefore, the graph clearly indicates that HEPA-Net provides more reliable and accurate results for skin disease prediction**.**

V. Conclusion:

This paper presents an intelligent skin disease detection system using the proposed **HEPA-Net framework**, which integrates Histogram Equalization, preprocessing, data augmentation, and EfficientNetB0 to enhance feature extraction and improve classification performance. The proposed model achieves **96% accuracy** with improved precision, recall, and F1-score, outperforming existing models such as ResNet, CNN, VGG16, and U-Net, and enabling early and automated detection of skin diseases. The system also provides a user-friendly interface for image upload and real-time prediction, making it suitable for both clinical and remote healthcare applications while reducing manual effort and supporting faster decision-making. However, the system has certain limitations, including dependency on dataset quality, limited availability of rare skin disease images, and variations in lighting conditions, skin tone, and image resolution that may affect prediction accuracy. Additionally, the model relies only on image-based analysis without incorporating patient medical history. Future work includes expanding the dataset, enabling mobile and cloud-based deployment, enhancing explainability, and integrating advanced features such as severity analysis and treatment recommendation. Overall, the proposed HEPA-Net framework provides an accurate, efficient, and scalable solution for automated skin disease detection.

Reference:

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