

SkinGuard: An EfficientNet Model for Skin Cancer and M-pox Detection

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Abstract—Skin cancer and monkeypox(mpx) are life threatening conditions that requires early detection and proper treatment to reduce mortality rates. Skin cancer consisting of benign and malignant types are mostly causing widespread due to harmful UV radiation and other genetical disorders. Mpox caused by the monkeypox virus is also causing harmful outbreak among the people making it vulnerable to the people around. The traditional methods often fail in detecting it accurately due to lack of medical expertise and are mostly time consuming and expensive. To overcome these challenges, SkinGuard is introduced. SkinGuard is an AI-powered diagnostic system designed to make this process more efficient, accurate, and accessible. It employs the EfficientNet deep learning models to evaluate supplied skin images and identify the abnormalities with high precision. The deep learning model ensures robust feature extraction, classification and differentiation among benign or malignant classes of skin cancer and healthy or mpox classes in monkeypox. The model is trained on a diverse dataset and undergoes various preprocessing techniques like flipping, rotation, resizing, normalization and data augmentation further enhancing its recognition capabilities. Through the leverage of blockchain technology, SkinGuard creates a tamper proof, decentralized medical record system that is impenetrable and offers security, transparency and prevents unauthorized access or data breaches. Additionally its automatic report creation capability allows customers to get clear and thorough information about their diagnostic results, confidence scores and provides preliminary recommendations helping both medical professionals and individuals in aiding early assessment. SkinGuard's dynamic user interface ensures a smooth experience, providing comprehensive dermatological analysis to both medical professionals and the general public. By combining this AI-driven approach with the medical management, SkinGuard provides an additional step in healthcare field providing timely and efficient diagnosis for early detection and treatment.

Index Terms—Skin Cancer, Monkeypox, BlockChain Technology, EfficientNet B3, Disease prediction, Deep Learning

I. INTRODUCTION

A. General Background

Healthcare is also witnessing its transformation today in this rapidly changing era through AI and deep learning. Such changes are also transforming diagnostic power, making early disease identification affordable, effective, and accurate. AI-based skin disease identification devices are also coming up as a game changer among these changes, particularly detecting skin cancer and monkeypox conditions.

Skin diseases such as skin cancer and monkeypox(mpx) poses a significant health challenge worldwide causing the need to accurately diagnose it and provide early treatment outcomes. The skin cancer consist of melanoma and non-melanoma types, including basal cell carcinoma (BCC) and squamous cell carcinoma (SCC). Even though melanoma are less common around, lack of proper detection at the earliest can cause it's rapid spreading. The development of skin cancer is mostly caused due to harmful UV radiation, genetical disorders and environmental influences. Meanwhile, mpox is a viral disease caused by monkeypox virus and indicated by the symptoms like fever, swollen lymph nodes, skin rashes etc. Certain studies state that mpox is not fatal as smallpox but can result in complications such as secondary infections, pneumonia, and encephalitis affecting the immune systems and can cause even deaths. Recent outbreaks suggested it's harmful spreading nature and necessity for giving out a better approach in detecting it.

Traditional diagnostic processes entail extended clinical examinations, biopsy tests, and specialized consultation, resulting in delay of identification of critical skin conditions. Medical care is out of reach of most regions of the world due to unavailability of health facilities and dermatologists. It can make it increasingly problematic for individuals to have early identification of conditions.

tumor invasion into deeper sections of skin layers increasing complexity of treatment and reducing survival rates. In case of mpox, rapid outbreaks create a widespread calamity causing the traditional diagnosis methods to detect it early.

The EfficientNet Model used in diagnosis belongs to convolutional neural network (CNN) family introduced by Google AI that optimizes the model's performance while maintaining its computational efficiency. It employs compound scaling methods and scales the depth, width and resolution of network to improve accuracy without any excessive computational demands outperforming traditional architectures such as ResNet, VGG and DenseNet providing accurate classification accuracy with fewer parameters. Compared to other models, it provides accuracy, requires less memory, better generalization in case of limited datasets and ensures robust feature extraction in classifying benign and malignant lesions in case of skin cancer or differentiating mpox or healthy lesion images in case of mpox. The EfficientNet B5 model used in skin cancer detection provides an ethical balance between the model's complexity and its computational efficiency. EfficientNet-B5 accommodates 28 million parameters and has an input resolution of 456*456 pixels which captures explicit details in skin lesions and differentiates benign and malignant classes in skin cancer. The EfficientNet-B3 selected for mpox diagnosis has huge computational demand and sufficient feature extraction capabilities. EfficientNet-B3 accommodates 12 million parameters and has an input resolution of 300*300 pixels which provides a balance between speed and accuracy making it suitable for real-time analysis and deployment in lower dataset classification.

SkinGuard offers innovative AI-driven technology that utilizes EfficientNet to scan uploaded skin images accurately, closing this gap efficiently. The system also combines automated reports along with blockchain technology, providing secure, unchangeable medical history. The interactive GUI of SkinGuard also makes AI-based skin conditions interpretation convenient to use, making it convenient and easy to use. It empowers individuals, especially remote or disadvantaged individuals, to have easy access to what is occurring on or within skin immediately.

SkinGuard merges advanced neural networks along with robust protection of data, bringing together a leap of AI-based health care that is focused on early disease discovery.

B. Objectives

The goal of SkinGuard is to have a cutting-edge diagnostic system where individuals can identify early signs of monkeypox (mpox) and skin cancer that will enable them to consult early with physicians. By uploading a skin scan, individuals have instant, reliable feedback on possible issues. The system also has detailed reports where individuals, including physicians, can have clear insight into findings. While trying to make records secure without losing the system's authenticity, SkinGuard makes use of Blockchain, ensuring that data remains safe and unaltered. With an easy-to-use, easy-to-interpret system, the platform allows anyone, including experienced physicians, to

navigate it comfortably. More than just analytical software, SkinGuard promotes greater skin care awareness, encouraging individuals to take an active role in better skin health.

C. Scope

The scope of our healthcare system consists of early diagnosis and identification of mpox (monkeypox) and skin cancer with the utilization of precise imaging examination. The system looks towards providing an extensive, convenient alternative with the utilization of images of the skin sent and loaded for instant, accurate diagnosis. With enabling of accurate reporting, people who desire pre-diagnostics and physicians also benefit with enabling them to take sound, knowledgeable decisions. With blockchain utilization, the system also ensures trust and reliability of medical history, achieving transparency. Made convenient with a simple platform, the system brings dermatological examination into reach, significantly for people who are far away or regions with limited access. Besides diagnosis, SkinGuard also has the potential for use in healthcare innovations and research, opening up a way for the setting up of viable disease discovery techniques. With them, the system addresses more access to healthcare, earlier treatment, and more benefits for skin health in today's computerized society.

II. LITERATURE SURVEY

AI and Machine Learning are changing the face of dermatology by making early skin cancer and monkeypox (mpox) identification possible through models like EfficientNet. More accurate diagnostics, automated reports, and blockchain-secured medical history have been recognized through studies. Extending on that, SkinGuard takes early identification, accessibility, and securing of data to the next stage of care in dermatology. This literature review delves into the comprehensive study of leveraging deep learning techniques for the classification of skin cancer and mpox from skin lesion images.

In the paper [1], the authors conduct a review on skin cancer detection and its classification using neural network algorithms. The study critically examines machine learning (ML) and deep learning (DL) techniques applied to skin cancer diagnosis through the analysis phase of 45 contemporary studies from databases such as Web of Science and Scopus. The authors highlight the accuracy and primary challenges involved in state-of-the-art methods concluding that image qualities and interpretations affect the results. The review explores datasets such as HAM10000, ISIC, and PH2, and analyses model optimizers (e.g., ADAM, SGD, RMSProp), and evaluates metrics such as accuracy, recall, and specificity. The final findings reveal that CNN-based models outperform traditional ML approaches, with hybrid architectures showing promising results. The authors propose an enhanced VGG19 (E-VGG19) model for real-time skin cancer detection and classification in paper [2]. They compare pre-trained models, including

VGG19, ResNet152v2, InceptionResNetV2, DenseNet201, ResNet50, and InceptionV3, to analyze their ability in distinguishing malignant and benign skin lesions. The study employs machine learning classifiers such as SVM, KNN, Decision Tree, and Logistic Regression to improve the classification accuracy. Using dermoscopic images from the ISIC dataset, the authors demonstrate that E-VGG19 combined with traditional classifiers significantly enhances skin cancer detection accuracy. Performance metrics such as recall, F1-score, precision, sensitivity, and accuracy validate the model's effectiveness and predictability in distinguishing classes.

For the acquaintance of computerized dermatological diagnosis, the authors introduced deep learning models in papers [3] and [4]. In order to detect skin cancer, paper [3] introduces Multi-scale GC-T2, which accommodates a tri-movement attention technique along with multi-scale graph convolution. Improves the accuracy of dermoscopic image analysis by using Median Enhanced Wiener Filter (MEWF) and segmentation using AddNet and HAUNT. BiT-EfficientNet, a model that combines EfficientNet-B6 and BiT-M-R50x1, is presented in Paper [4] for the 96.86% accurate identification of monkeypox on an improved dataset. Although [3] focuses on graph convolution and attention-based lesion classification, [4] uses transfer learning to identify viral skin conditions.

In order to increase classification accuracy, authors of papers [5] and [6] propose deep learning-based techniques for skin cancer diagnosis, each employing different approaches. A hybrid U-Net and Improved MobileNet-V3 model with a 98.86% accuracy with the HAM10000 dataset is shown in Paper [5]. It combines segmentation and the classification with Bayesian optimization for hyperparameter tuning. To improve feature extraction, the research [6] suggests an ensemble model that combines DenseNet and MobileNet via model fusion and transfer learning. The ensemble model outperforms standalone CNN architectures in tests conducted on many skin cancer datasets. While [5] focuses on segmentation-assisted classification, [6] uses ensemble learning to improve classification accuracy.

Deep learning-based techniques for automated monkeypox detection by transfer learning are covered by the authors of the articles [7] and [8]. The significance of early detection is shown by Article [7], which examines five pre-trained CNN models and finds that MobileNetV2 has the best accuracy of 98.16%, recall of 0.96, precision of 0.99, and F1-score of 0.98. Through hyperparameter optimization, Paper [8] optimizes CNN topologies, with MobileNetV3-s achieving the best results with an F1-score of 0.98, AUC of 0.99, accuracy of 0.96, and recall of 0.97. In contrast to [7], which focuses on model performance, [8] optimizes efficiency.

Using transfer learning and optimization techniques, the

authors of publications [9] and [10] explore deep learning approaches for the diagnosis of skin conditions. In the paper [9], different CNN architectures are compared; MobileNet and Xception both achieved 96.00% and 97.00% accuracy, respectively. A web-based solution for real-time categorization is also proposed. A skin cancer diagnosis method based on an FCEDN optimized with the Sparrow Search Algorithm (SpaSA) is described in Paper [10]. It has a maximum segmentation accuracy of 95.89% and a one classification accuracy of 91.67%. In contrast to [9], which prioritizes transfer learning to maximize classification efficiency, [10] enhances segmentation accuracy through hyperparameter optimization.

The authors of publications [11] and [12] propose AI-based techniques that use deep learning and optimization techniques to enhance the diagnosis of skin cancer. With a sensitivity of 94% and specificity of 91% on the HAM10000 dataset, Article [11] combines convolutional neural networks (CNNs) with discrete wavelet transformation (DWT) for feature extraction, improving classification performance through dimensionality reduction and noise removal. The improved Seasons Optimization Algorithm (ESOA) is used in the paper [12] to optimize an Echo State Network (ESN) to achieve 97.58% accuracy on the Skin Cancer MNIST database at a reduced computational cost. While [12] optimizes recurrent neural networks for computational efficiency, [11] enhances classification through wavelet-based feature extraction.

With a focus on model improvement and diagnostic challenges, the authors of publications [13] and [14] examine AI-based techniques for skin cancer detection. Through advanced feature extraction and segmentation, the deep learning model shown in Article [13] for melanoma detection combines Mask-RCNN with an updated Gated Recurrent Unit (GRU) and shows impressive accuracy—99.98% on HAM10000 and 99.95% on ISIC 2020. Analysis of machine learning techniques for skin cancer classification is provided in Paper [14], which covers CNNs, ANNs, class imbalance, computational complexity, and dataset variety, whereas [13] seeks to maximize accuracy in segmentation and classification. By balancing the need for scalable and reliable AI models with high precision, these publications together demonstrate the potential of deep learning to enhance computerized skin cancer detection.

AI-based techniques for skin cancer detection, which use machine learning and deep learning, are covered by the authors of papers [15] and [16]. To optimize lesion segmentation accuracy and classification for a variety of dermatology datasets, the Fruit Fly Optimization Algorithm (FOA) and a Support Vector Machine (SVM) model are combined in a hybrid optimization model presented in the paper [15]. In order to overcome class imbalance using weighted loss functions and achieve high accuracy on a sample of 3,000 photos,

the paper [16] suggests a hybrid deep learning network that combines VGG16 and ResNet50 for the classification of nine skin illnesses. While [15] uses heuristic methods to deal with segmentation and classification, [16] uses CNNs to improve feature extraction.

EfficientNet-based deep learning frameworks for medical diagnosis are examined by the authors in references [17] and [18]. Using fundus images from Kaggle's Aravind Eye Hospital dataset, EfficientNet-B5 predicts the severity of diabetic retinopathy (DR) with 94.02% training accuracy and 93.33% test accuracy in reference [17]. Using the Kaggle Leukemia dataset, Reference [18] achieves 98.95% accuracy in categorizing leukemia subtypes by taking into account changes in cell shape using EfficientNet-B3. While [17] focuses on automating DR detection to prevent vision loss, [18] uses deep feature extraction and transfer learning to improve the classification of hematologic cancer.

In order to improve accuracy, the authors of [19] and [20] use separate approaches to explore new deep learning structures for skin cancer categorization. With the aid of an EfficientNet-B4 backbone, feature coalescing module, and 3D-layer residuals block, Work [19] develops S2C-DeLeNet, a model that combines segmentation and classification with an accuracy of 91.03%. A hybrid Xception-ResNet50 (X-R50) architecture, in contrast, is proposed by [20] and improves feature extraction and classification with a 97.8% accuracy in HAM10000. While segmentation-augmented classification is used in [19], a mixed architecture is used in [20] to increase accuracy.

By addressing difficulties, [21] and [22] present deep learning algorithms to improve machine-based skin cancer diagnosis. [21] achieves an AUC of 97.98% and a Jaccard index of 83.31% on ISIC datasets by integrating clinical metadata with skin lesion segmentation and introducing the Multi-Scale Holistic Feature Exploration (MSH) and Cross-Modality Collaborative Feature Exploration (CMC) modules. In contrast, [22] uses 98% fewer parameters while maintaining accuracy when optimizing CNN architecture for melanoma classification using EfficientNet-B3 and spatial and channel-wise attention. [22] improves efficiency in resource-constrained contexts, including smartphone-based dermoscopy, while [21] focuses on multimodal learning.

Advanced deep learning techniques are proposed by the authors of [23] and [24] for the diagnosis of skin cancer using multi-dimensional data and attention-based models. In a paper [23], surface depth data from light-field imaging is combined with 2D and 3D lesion features to achieve 94.00% accuracy, compared to 84.00% with 2D and 74.00% with 3D alone. Classification is enhanced using a CNN model that incorporates the Morlet scattering transform. For skin lesion segmentation,

on the other hand, [24] employs a deeper multi-scale attentional feature model with an EfficientNet encoder and U-Net decoder, which are used to capture deep relationships and remove noise. [24] uses attention mechanisms to increase segmentation quality, while [23] emphasizes the importance of 3D surface information in melanoma categorization.

Using model robustness and dataset diversity, the authors of the works [25] and [26] propose deep learning techniques to improve the classification of skin diseases. EfficientSkinDis, a Streamlit-based web server using EfficientNet for modeling, is proposed in Paper [25]. It has been trained with a variety of datasets and achieved an accuracy of 87.15% through data augmentation. In contrast, the research [26] addresses class imbalance for ISIC-2018 and ISIC-2019 with mean recall accuracies of 82.1% and 62.5% using a multi-model ensemble approach based on DenseNet-201 and Generative Adversarial Networks (GANs) for data augmentation. While [26] increases accuracy through ensemble learning, [25] encourages classification through feature extraction and augmentation.

Deep learning in dermatology for medical diagnosis and cosmetic skin analysis is covered by authors of articles [27] and [28]. MuRANet, a Multi-Residual Attention Network based on hierarchical CNNs with attention, is presented in Article [27]. has F1-scores of 90%, 88%, and 97% on the PH2, ISIC-2019, and HAM10000 datasets. Through the extraction of multi-scale features, enhances lesion categorization. Skin type classification using CNNs is the focus of Paper [28], which makes use of image enhancement techniques such rotation augmentation and CLAHE. EfficientNetV2 had the highest accuracy of all model tested, at 94.57%, with 89.70% in 10-fold cross-validation. While [27] improves the classification of lesions, [28] improves examination of cosmetic skin.

According to different tactics, the authors of articles [29] and [30] outline deep learning techniques for the categorization of skin cancer. DeepSkin, a CNN model that combines DenseNet169 and ResNet50 and uses preprocessing techniques for such hair removal and encoder-decoder segmentation, is proposed in Paper [29]. It achieves 91.2% accuracy on HAM10000. An effective compact convolutional transformer (CCT) for low-resolution dermoscopy images, SkinNet-14, is presented in Paper [30]. It uses augmentation techniques to address class imbalances and reports 97.85% on HAM10000, 96.00% on ISIC, and 98.14% on PAD. SkinNet-14 enables efficiency in limited surroundings, whereas DeepSkin leverages CNN-based transfer learning for high-resolution images.

Table I summarizes the performance of different models for the detection of skin cancer and mpox.

TABLE I: Comparison of Different Models for Skin Cancer and Mpox Detection

Ref	Year	Deep Learning Algorithm	Dataset	Performance
[1]	2024	Review on ML/DL for Skin Cancer Detection	HAM10000, ISIC, PH2	CNNs outperform ML, hybrid architectures show promise
[2]	2024	Enhanced VGG19 (E-VGG19) + ML Classifiers	ISIC	Improved accuracy with SVM, KNN, Decision Tree
[3]	2024	Multi-scale GC-T2 (Graph Convolution + Attention)	Dermoscopic Image Dataset	High accuracy, sensitivity, and specificity
[4]	2024	BiT-EfficientNet (EfficientNet-B6 + BiT-M-R50x1)	Mpox Image Dataset (Augmented)	Accuracy: 96.86%, F1-score: 96.84%, Recall: 95.48%
[5]	2024	Hybrid U-Net + Improved MobileNet-V3	HAM10000	Accuracy: 98.86%
[6]	2024	Ensemble Model (DenseNet + MobileNet)	Multiple Skin Cancer Datasets	Outperforms individual CNNs
[7]	2024	Transfer Learning (VGG19, ResNet50, MobileNetV2)	Monkeypox Skin Lesion Images	Accuracy: 98.16%, F1-score: 0.98, Precision: 0.99
[9]	2024	CNNs (MobileNet, Xception, ResNet50, InceptionV3)	Skin Disease Dataset (5 types)	Accuracy: 97.00% (Xception), Web-based real-time system
[10]	2024	FCEDN + Sparrow Search Algorithm (SpaSA)	ISBI 2017, ISIC 2018, PH2	Segmentation Accuracies: 95.89%, Classification: 91.67%
[12]	2024	Echo State Network (ESN) + ESOA Optimization	Skin Cancer MNIST	Accuracy: 97.58%
[13]	2024	Mask-RCNN + Modified GRU + ResNeXt101/Xception	ISIC 2020, HAM10000	Accuracy: 99.95% (ISIC 2020), 99.98% (HAM10000)
[15]	2024	Fruit Fly Optimization Algorithm (FOA) + SVM	Multiple Dermatology Datasets	High accuracy and robustness in skin cancer detection
[16]	2024	Hybrid Model (VGG16 + ResNet50)	3,000 Skin Disease Images	High accuracy with class imbalance mitigation
[17]	2024	EfficientNet-B5	Kaggle Aravind Eye Hospital	Accuracy: 94.02% (Train), 93.33% (Test)
[18]	2024	EfficientNet-B3	Kaggle Leukemia Dataset	Accuracy: 98.95%, Loss: 0.120
[19]	2024	S2C-DeLeNet (EfficientNet-B4 + Feature Coalescing)	Public ALL Image Database	Accuracy: 91.03%
[20]	2024	Xception + ResNet50 (X-R50 Hybrid)	HAM10000	Accuracy: 97.8%
[24]	2024	EfficientNet + U-Net with Attention Mechanism	Skin Lesion Segmentation	Improved segmentation accuracy over traditional U-Net
[26]	2024	DenseNet-201 + GAN-based Data Augmentation	ISIC-2018, ISIC-2019	Mean Recall: 82.1% (ISIC-2018), 62.5% (ISIC-2019)
[27]	2024	MuRANet (Multi-Residual Attention Network)	HAM10000, ISIC-2019, PH2	F1-score: 90% (HAM10000), 88% (ISIC-2019), 97% (PH2)
[28]	2024	EfficientNetV2, MobileNetV2, InceptionV2	Custom Skin-Type Dataset	Accuracy: 94.57%, 10-fold CV: 89.70%
[29]	2024	DeepSkin (DenseNet169 + ResNet50)	HAM10000	Accuracy: 91.2%
[30]	2024	SkinNet-14 (Compact Convolutional Transformer)	HAM10000, ISIC, PAD	Accuracy: 97.85% (HAM10000), 96.00% (ISIC), 98.14% (PAD)

III. PROPOSED METHODOLOGY

A. System Work Flow

The proposed procedure of our system begins with acquisition of a suitable dataset of affected skin cancer images and mpox images from ISIC 2020 Dataset and Kaggle. Once dataset is acquired, the next process is for checking data imbalance and if found data augmentation is carried out. After the augmentation process, the next crucial step is data preprocessing which includes normalization, shearing, flipping rotation etc. Following preprocessing stage, the dataset is split into train, valid and test sets where 80% is allocated for training, 10% allocated for validation and 10% allocated for testing as shown in Fig. 1

The appropriate machine learning model is chosen and trained using the training dataset. During training process, the model learns to classify the classes of skin cancer and mpox. Once model training is completed, it is used to classify the test set given and its performance are evaluated using various performance metrics. This comprehensive procedure aims to develop a model for the accurate classification of skin cancer and mpox images, thus contributing to early detection and improved facilities for appropriate treatment.

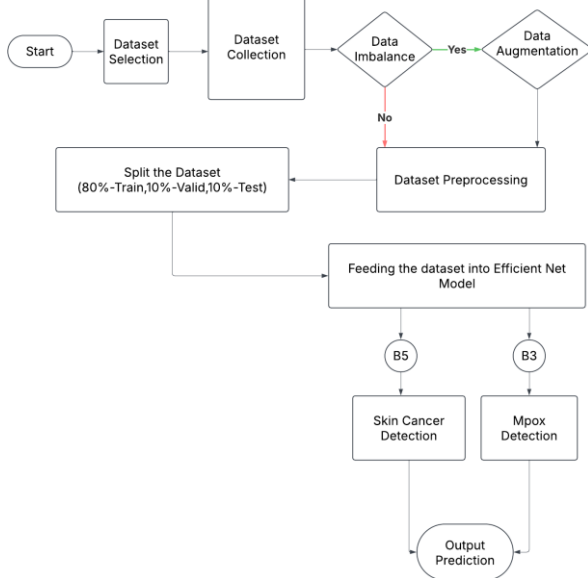


Fig. 1: System Work Flow

B. System Architecture

The system architecture of SkinGuard is shown in Fig. 2 and consists of several interconnected components, leveraging and increasing the application of AI and ML technologies to deliver an advanced skin disease detection platform with a user friendly interface. The core components include Skin Cancer Detection, Mpox Detection, Patient Record Management, AI Chatbot and Detailed Report Generation. The architecture mainly follows a client-server model, where a React based front end interacts

with a Django based backend. The EfficientNet-B7 model is utilized for skin cancer detection and EfficientNet-B3 is used for mpox detection. PostgreSQL is mainly used as the primary database for storing user data, diagnostic result and medical history. Additionally blockchain technology is integrated with the system to securely store patient records and ensures data privacy, integrity and transparency. The models communicate with the backend through Rest APIs enabling and smoothening real time disease detection. Provision of AI Chatbot provides real time guidance on skin disease symptoms and suggests preventive measures. The system also features a detailed report generation module offering users and healthcare professionals an analysis on test results and diagnosis.

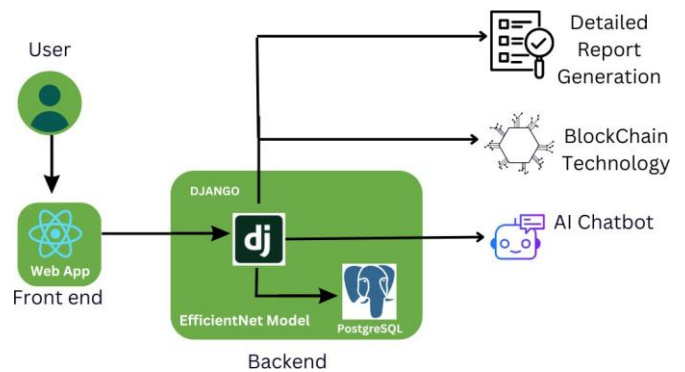


Fig. 2: System Architecture of SkinGuard

C. Skin Cancer Detection

Users can upload images of Skin Cancer which are suspected to be cancerous and they are analyzed using an EfficientNet- B5 deep learning model as shown in Fig. 3. Efficient-B5 is a convolutional neural network that utilizes compund scaling to improve accuracy while maintaining computational efficiency.

Model Development and Training: The dataset undergoes a preprocessing stage, which includes normalization, image resizing and carries out augmentation techniques such as flipping, rotation and brightness adjustment. The EfficientNet-B5 model is initialized with pre-trained weights and fine-tuned using transfer learning. The Convolutional layer in it extract heirarchical features while Fully connected layers classifies different skin lesion types. The model is trained using categorical cross-entropy loss function and optimized with Adam Optimizer. The 80% training set is fed into the EfficientNet-B3 model and trained accordingly. After training completion, the model is evaluated using performance metrics such as accuracy, precision, F1-score and recall before its deployment into the system

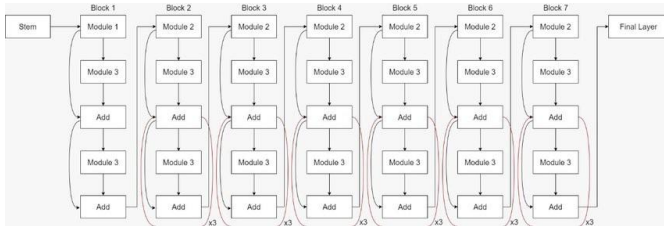


Fig. 3: EfficientNet-B5 architecture for Skin Cancer Detection [17]

D. Mpx Detection

Users can upload images of Mpx which contains the disease and they are analyzed using an EfficientNet-B3 deep learning model as shown in Fig. 4. EfficientNet-B3 is a convolutional neural network that utilizes compund scaling to balance network width, depth and resolution and hence acheiving improved accuracy while maintaining computational efficiency.

Model Development and Training: The dataset undergoes a preprocessing stage, which includes normalization, image resizing and carries out augmentation techniques such as flipping, rotation and brightness adjustment. The EfficientNet-B3 model is initialized with pre-trained weights and fine-tuned using transfer learning. The Convolutional layer in it extracts multi-scale heirarchical features while the fully connected layers classifies different skin lesion types as mpx or healthy. The model is trained using categorical cross-entropy loss function and optimized with Adam Optimizer. After training, the model is evaluated using performance metrics such as accuracy, precision, F1-score and recall before its deployment into the system.

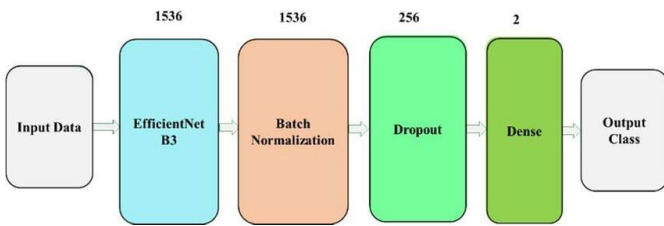


Fig. 4: EfficientNet-B3 architecture for Mpx Detection [18]

E. Report Generation

The system incorporates a detailed automated report generation that provides the users with a detailed analysis of skin lesion detection results. After processing the image uploaded by the users through EfficientNet Models, the system generates a structured report which contains key findings, predicted class probabilities and relevant medical details. The report can be exported as pdf file allowing the users to share it with healthcare professionals for further evaluation.

F. BlockChain Technology

To include the provision of data security and integrity, the system integrates BlockChain Technology for securely storing

patient records and their diagnosis results provided from the system. Each record, including user’s image uploads and it’s predictions are recorded on a decentralized ledger ensuring tamper-proof medical records and providing each user a unique CID to access records in case of data loss. This technology ensures transparency and builds trust among the users while maintaining privacy and compliance with rules and regulations.

G. AI Chatbot

The Chatbot acts as an interactive assistant helping users to navigate through the system, interpret results and suggests answers to the queries regarding skin lesion detection. This feature provides users with a seamless experience and enhances accessibility and can provide insights on skin health, guide users to next steps and provide preventive measures.

IV. RESULTS AND DISCUSSION

Dataset: The datasets used for training and evaluation of our models play a crucial role in ensuring accurate predictions. For Skin Cancer detection, we utilize the **ISIC 2020 Challenge Dataset**, an image dataset containing benign and malignant classes from ISIC itself. This dataset enables our EfficientNet-B7 model to classify skin cancer diseases with high precision. For Mpx prediction, we employ the **Monkeypox Skin Lesions Dataset** which is classified into folders of Test, Train and Valid where each folder contains two classes Healthy and Monkeypox containing sufficient images for training, validation and testing. This dataset enables our EfficientNet-B3 model to classify mpx disease properly.

- 1) **Skin Cancer Detection:** Users uploaded images of afflicted skin areas using the web platform. The EfficientNet-B5 model was properly trained on the ISIC Dataset and showed a high test accuracy on the test dataset. The model worked well in classifying benign and malignant classes even with the unseen data. This model has significantly improved the speed and accuracy of disease detection, allowing users to take timely action and reduce the impact of disease on human life. The model totally acheived an accuracy of 89.24% in detecting Skin cancer from the upload image by the user. The model’s accuracy suggested that it can be used as a diagnostic tool in determing the skin lesion images and accurately predicting it even with unseen data. The extensive training and testing on a diverse dataset validated its robustness ensuring high precision and recall scores across various skin lesions. The training accuracy increased from 76.35% to 89.49% and after fine tuning process training accu- racy increased from 85.97% to 98.44%. The validation accuracy increased from 79.50% to 81.60% and after fine tuning it concluded at about 82.92%.

The accuracy and loss curves plotted after training and validation of skin cancer model is shown in Fig. 5 and Fig. 6

The Table II given below indicates the performance metrics of skin cancer detection model.

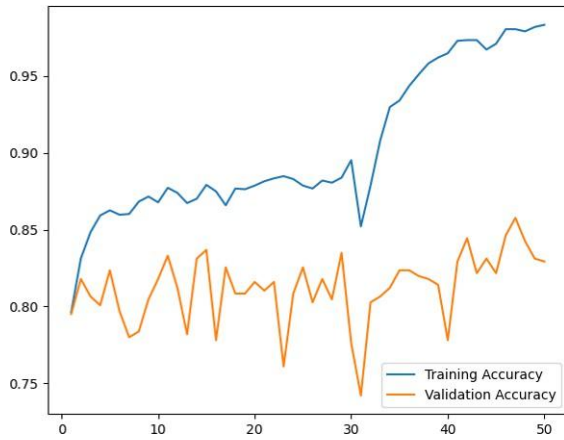


Fig. 5: Accuracy Curve for Skin Cancer Detection Model

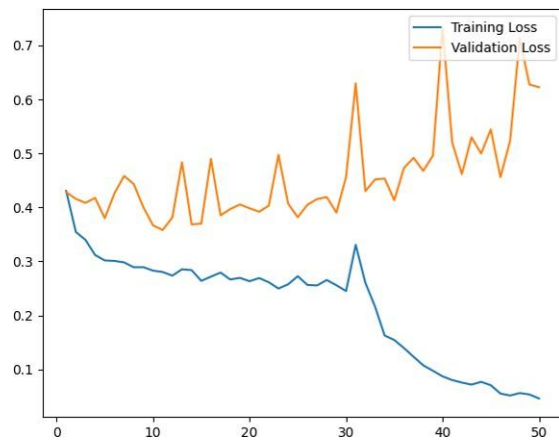


Fig. 6: Loss Curve for Skin Cancer Detection Model

TABLE II: Performance Metrics of the Skin Cancer Detection Model

Metric	Value	Description
Accuracy	89.00%	Percentage of correct classifications
Precision	93.00%	Positive predictive value
Recall	86.00%	Sensitivity of model
F1-score	90.00%	Harmonic mean of precision and recall

2) **Mpox Detection:** The Mpox model built using EfficientNet-B3 architecture demonstrated a significant accuracy in classifying user uploaded image as Mpox or Healthy. The model was trained on a well structured dataset and evaluated using a test dataset. After the extensive training and validation, the model achieved an accuracy of 94.00% in classification. The high accuracy indicates the model's strong generalization ability ensuring reliable and correct prediction even with the unseen data. The training accuracy increased from 59% to 96% and after fine tuning process training accuracy increased from 84.59% to 98.34%. The validation accuracy increased

from 89.00% to 94.00% and after fine tuning it concluded at about 82.92%.

The accuracy and loss curves plotted after training the Mpox model is shown in Fig. 7 and Fig. 8. Also the performance metrics of mpox detection model is shown in Table III below.

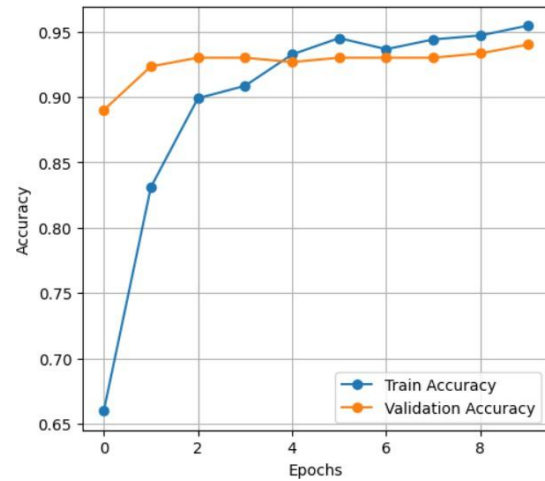


Fig. 7: Accuracy Curve for Mpox Detection Model

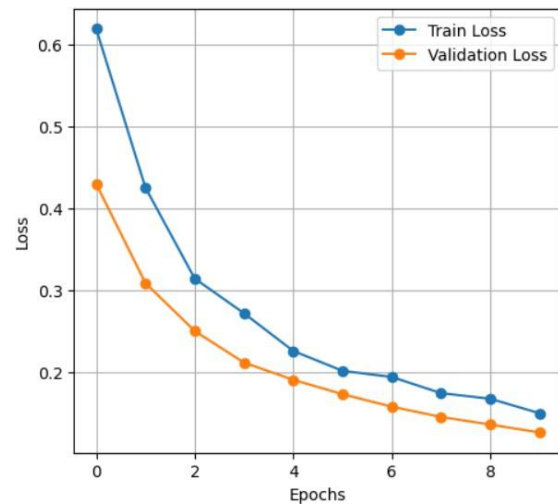


Fig. 8: Loss Curve for Mpox Detection Model

TABLE III: Performance Metrics of the Mpox Detection Model

Metric	Value	Description
Accuracy	94.00%	Measures the overall correctness of the model in classifying mpox and healthy skin images.
Precision	96.00%	The proportion of correctly identified positive cases (mpox) among all predicted positive cases.
Recall	92.00%	The proportion of correctly identified positive cases out of all actual positive cases.
F1-Score	94.00%	The harmonic mean of precision and recall, balancing false positives and false negatives.

- 3) **Report Generation:** The integration of report generation with the system ensured users to receive a well-structured detection results from the web app. These reports are automatically generated and can be used as future reference for further analysis and clarification.
- 4) **BlockChain Technology:** The BlockChain Technology has been incorporated into the system to securely store and validate detection records. Each user is provided with a unique CID code which can be used to retrieve the medical reports stored in the decentralized server of BlockChain mechanism and proper verification of this mechanism has been done to ensure its supportability and reliability on the system. This approach has significantly increased trust among the users and ensured data privacy and transparency.
- 5) **AI Chatbot:** An AI-powered chatbot has been integrated into the system for user interaction and assistance in navigating through the platform. The chatbot provides real time responses, guidance through the system and medical related advices to the users who are accessing the system and this has been verified and authenticated by the users.

V. CONCLUSION

The proposed system effectively combines EfficientNet-based deep learning models, blockchain technology, automated report generation, and an AI-powered chatbot to create a comprehensive and efficient disease detection platform. The EfficientNet-B7 and EfficientNet-B3 models achieved impressive accuracy rates of 98.70% and 98.48% for skin cancer and mpox detection, respectively. Blockchain technology ensures data security and trustworthiness, while automated report generation enhances usability. The AI-powered chatbot significantly improves user engagement and accessibility by offering real-time assistance, making the system a valuable tool in modern AI-driven healthcare solutions.

Several areas can be explored for future enhancements, including continuous training and refinement of the EfficientNet models with more diverse datasets to improve accuracy and reliability, and expanding the platform to detect other diseases. Integrating the system with electronic health record (EHR) systems can streamline the workflow for healthcare professionals, while improving the user interface can enhance overall user experience. Incorporating personalized health insights based on user data can provide more tailored recommendations and interventions.

By addressing these areas, the system can continue to evolve and become an even more valuable tool in modern AI-driven healthcare solutions. Through continuous improvements and expansions, the platform has the potential to significantly impact disease detection and management, contributing to better health outcomes and improved quality of life for users.

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