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Research Article

The Detection of Skin Dermatology Disease with an improved Activation Function in Deep Learning

Shamira Arshad Shaikh [1], Dr. Yogita Mistry [2]
[1]*Research Scholar, Department of Electronics and Telecommunication, Ramrao Adik Institute of Technology, Nerul (Navi Mumbai), Maharashtra, 400706*
Email: syed.sameera222@gmail.com
[2]*Associate Professor, Department of Information Technology, Ramrao Adik Institute of Technology, Nerul (Navi Mumbai), Maharashtra, 400706*
Email: yogita.mistry@rait.ac.in

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ABSTRACT

Introduction: Skin dermatological diseases are among the most prevalent health concerns worldwide, affecting individuals across various age groups and demographics. Traditional diagnostic methods—such as visual inspection and manual assessment—are often subjective, time-consuming, and prone to inconsistencies due to variability in the examiner's expertise. These limitations call for more objective and automated approaches to enhance the accuracy and efficiency of dermatological diagnostics

Objectives: This research aims to develop a stable and effective classifier for dermatological diseases using deep learning. The specific objectives include reshaping the dataset, addressing class imbalance using SMOTE, comparing the performance of various deep learning models, and identifying the most accurate model for skin disease classification.

Methods: A balanced dataset consisting of eight classes of skin diseases was used for the study. Data preprocessing techniques were applied, including the use of Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance. Three deep learning models—CNN, VGG16, and EfficientNet-B2—were trained and evaluated for performance. Model fine-tuning was carried out to optimize classification accuracy.

Results: Among the models tested, EfficientNet-B2 achieved the highest accuracy of 84%, demonstrating its superior architectural efficiency for the classification task. The findings also highlighted the importance of data preprocessing and model fine-tuning in achieving robust diagnostic performance.

Conclusions: This study demonstrates that deep learning models, particularly EfficientNet-B2, can significantly improve the accuracy and efficiency of dermatological disease classification. The results suggest that proper data handling and model optimization are crucial in overcoming the limitations of traditional diagnostic methods. Future work will explore the integration of attention mechanisms with the Inception model to further enhance diagnostic capabilities.

Keywords: Skin Dermatology Diseases, Deep Learning, Medical Image Analysis, Automated Diagnosis, Convolutional Neural Networks (CNN), Synthetic Minority Oversampling Technique (SMOTE).

INTRODUCTION

Skin dermatology diseases refer to a large group of disorders covering the skin, an important external organ of the human body acting as a shield against environmental aggressors [1]. These diseases may present as infections, inflammation, allergies, autoimmune responses, or malignancies and present diagnostic and therapeutic difficulties [2]. Non-cancerous skin conditions include acne, psoriasis, eczema, dermatitis, and fungal diseases, whereas cancerous diseases include melanomas, basal cell carcinoma, and squamous cell carcinoma [3].

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Research Article

Dermatology diseases are not only skin diseases but also influence the patient's mental and physical well-being, considering that symptoms such as rashes, lesions, discoloration, or scaling are evident over the skin [4]. The causes of these illnesses include heredity, toxicity, diet, exercise, and immune deficiencies, and rows are other factors that may cause these conditions. For example, UV radiation may cause skin cancer; allergens/irritants cause eczema/dermatitis, and so on. Identifying a disease at an early stage and especially determining whether it is a malignant one at an early stage is very important, given that delay can be fatal.

The more conventional techniques involve mainly macroscopic examination of the tissues, followed by biopsy, which may be tedious and costly. However, the use of technology, especially artificial intelligence and deep learning, has changed how skin diseases are diagnosed [5]. Utilizing deep dermoscopic images enables these systems of AI to properly search for established patterns that can then tell the difference and categorize the skin diseases, in most cases doing so with a higher success rate than professionally skilled dermatologists.

These systems also improve the speed and availability of diagnosis while also showing potential for implementation in resource-scarce and distant environments. The rate of skin diseases is rapidly increasing worldwide because of factors such as an ageing population, urbanization, and increased exposure to UV radiation, and thus fresh ideas should be adopted. Establishing dermatology in a civilized society as a hub to avail the advantage of early, accurate, and non-invasive diagnosis is paving the way to transform dermatology to unlock the burden of skin diseases.

LITERATURE REVIEW

The first study, which has been given by [6], discusses rising incidences of skin diseases and explains that skin diseases are invasive, posing a threat of causing lethal repercussions with every 1.79% of the global population being victims, and hence underlines the need for prompt diagnosis to avoid utmost risks of life threats. The researchers suggest an expert system using 50 layers of Residual Neural Network (ResNet) to detect essential skin diseases like eczema, psoriasis, benign tumors, and fungal and viral diseases. The system utilizes a dataset from DERMNET where model training and prediction are done using Python, achieving an accuracy of 0.95% at an epoch value of 10. It points out some weaknesses of the current diagnostic systems: inefficiencies and exclusive dependence on tests; that is why, the study aims to use machine learning to improve diagnostic abilities.

The research [7] is devoted to the creation of an intelligent system for skin disease classification, highlighting the problem of texturing and similarity between the diseases. With input parameters of a dataset of 25,331 clinical skin disease images and eight categories and an output of 8,238 images, lesion images, including vascular lesions, melanoma, basal cell carcinoma, and squamous cell carcinoma, were classified with a Residual Neural Network (ResNet-34). Data normalization, data augmentation, and the dropout method form part of the proposed model as a way of improving training effectiveness. By avoiding repeated information, ResNet-34 enhances training to have a high recall of 0.8331 and an accuracy of 92%, bettering other neural networks, including VGGNet.

According to [8], diagnosing serious skin conditions such as skin cancer has been made difficult by the fact that different diseases often present themselves similarly on the skin. To aid accurate and early detection, the researchers developed systems leveraging machine and deep learning techniques, evaluated on two datasets: ISIC 2018 and Pedro Hispano (PH2). The proposed approach was accomplished by adopting the following feature extraction methods: LBP and its variants, GLCM and its variants and DWT and its variants, to create a feature vector that was classified by the ANN and the FFNN classifiers. The FFNN proposed in this study was able to use the highest accuracy rates of 95.24% and 97.91% for the ISIC 2018 and PH2 datasets, respectively, when compared to other classifiers. Furthermore, the two models, ResNet-50 and AlexNet, were employed that use transfer learning; for ISIC 2018, ResNet-50 achieved a high level of accuracy at 90%, while for PH2, it was at 95.8%.

This study is given by [9], who contributes towards the fight against acne vulgaris, a disease that is caused by skin dryness and excess oil production affecting the mental, social, and self-emotional health of those affected, especially the teenagers. To help in the diagnosis and subsequent treatment, the scientists have designed the smartphone-based expert system referred to as Cureto using the hybrid deep convolutional neural networks (CNN) and natural language processing (NLP) approach. The system categorizes acne in terms of density and skin sensitivity, as well as special types such as whiteheads, blackheads, papules, pustules, nodules, and cysts, and recommends treatment levels for

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Research Article

patients according to the degrees of severities, patients' ages, genders, and other factors. The proposed system gives classification accuracy of 90-95% for acne types and 93-96% for skin sensitivity and acne density.

Study [10] aims to address the global rise in skin diseases by developing a computer vision-based system for detecting four types of skin diseases: chickenpox, measles, prickly heat, miliaria, erythema multiforme, psoriasis, rosacea, acne, keratosis, eczema herpeticum, and urticaria. The presented approach employs an 11-layer Convolutional Neural Network (CNN) consisting of convolutional, activation, pooling, fully connected, and softmax classifier layers. For validation, the established model was tested using the DermNet data source containing 30-60 samples per disease class. The study captured accurate classification rates of 98.6 percent to as high as 99.04 percent. Nevertheless, some issues that are considered obstacles to automating the detection process are skin color, position of diseases, and specification of image acquisition. The results of the study show that CNNs were effective in screening skin diseases, but the approach utilized data limits and specificity, which can limit their applicability across an array of skin diseases and populations.

The proposed study as given by [11] presents an automated image-based diagnostic system with the help of machine learning techniques to classify skin diseases effectively. This paper examines the difficulties of diagnosing skin disorders, most of which call for numerous tests and depend upon the skills of the attending physician. The technique includes pre-processing of skin images to eliminate noises and consequently improve image quality, and the feature extraction part of the framework employs the CNN. The extracted features are then used for diagnosis by the Softmax classifier, giving an analysis report with an accuracy of 87% attainment.

The MobileNet V2 model, which has been designed for lightweight computational devices, provides higher accuracy and reduced computations, making it appropriate for mobile applications, which is given by [12]. In this paper, the skin disease diagnosis approach added both MobileNet V2 and Long Short-Term Memory (LSTM) networks. Using a grey-level co-occurrence matrix (GLCM), the model measures the evolution of skin disease. The proposed method was also compared with other models, such as fine-tuned neural networks (FTNN), convolutional neural networks (CNN), and VGG with MobileNet V2, superior to others with more than 85% accuracy. The method is also faster as it takes nearly half the time of the conventional MobileNet model, hence cutting on computational actions. It was applied to the HAM10000 dataset and transformed into a mobile application for patients and dermatologists to quickly diagnose skin diseases from the images to avoid potential complications.

This study presented in [13] presents a new and stable skin cancer detection model based on feature fusion whereby skin lesions are distinguished as malignant or benign. The structure of the proposed system is as follows: low-level image enhancement with a Gaussian filter (GF) and manual and automatic feature extraction methods using local binary patterns and Inception V3, respectively. After that, the fused features are classified using a Long Short-Term Memory (LSTM) network. The performance incorporates elements of both machine learning and deep learning. For the Dermis dataset composed of 1000 images (500 benign and 500 malignant), the training set yielded a high accuracy of 99.4%, precision of 98.7%, recall of 98.66%, and F1-score of 98%. The model was also validated on the ISIC dataset, giving a detection accuracy of 98.4% through cross-validation. This study also shows that the proposed method is more accurate than the current segmentation-based and deep learning-based skin cancer detection methods.

The study [14] is specifically dedicated to the classification of the three types of skin cancer, which include basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma, based on the EfficientNet architecture. The images are scaled down to 256 x 256 pixels in the process data preparation stage before the images are used for training. The study uses various types of EfficientNet models ranging from EfficientNet-B0 to EfficientNet-B7 and then assesses the accuracy of the models. Another aspect explored in the work was the comparison of different models: The results were highest with the EfficientNet-B4 models with above 79.69% accuracy, 81.67% precision, 76.56% recall, and 79.03% F1-score. This suggests that the model EfficientNet has the feature of accurately predicting types of skin cancer.

Finally, a study [15] has proposed a new dataset of 31 skin diseases generated by merging two different datasets and uses deep learning for skin disease classification. Three models of CNNs, namely EfficientNet, ResNet, and VGG, have been adopted in the study through transfer learning. Among these, we found that the EfficientNet tested the

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Research Article

highest accuracy on the finer layers and improved the model further through additional adjustments. First, using a 70% training data split, the EfficientNet model reached a testing accuracy of 71%, and then augmented data samples boosted the testing accuracy to 72%. But a 70:30 split of the taken dataset was considered insignificant, and a split of 80:20 was carried out, and a test accuracy of 74% was achieved. Further augmentation of the data brought the accuracy up to 87.15%.

Table 1: Comparison Table

Study	Purpose	Techniques Used	Results	Limitations
[6]	Diagnosis of skin diseases like eczema, psoriasis, lichen planus, benign tumors, fungal infections, and viral infections using ResNet.	Residual Neural Networks (ResNet), DERMNET dataset	Achieved 95% accuracy with 10 epochs.	Limited to the DERMNET dataset, it may not generalize well for other datasets.
[7]	Classifying skin lesions such as Vascular lesions, Melanoma, Basal cell carcinoma, etc.	ResNet-34, Image Pre-processing, Data Augmentation, Dropout	Accuracy: 92%	High complexity due to the large variety of lesions and the need for significant computational power.
[8]	Early detection of skin diseases using two datasets (ISIC 2018, PH2).	Hybrid Features (LBP, GLCM, DWT), ANN, FFNN, CNN (ResNet-50, AlexNet)	ISIC 2018: 95.24%, PH2: 97.91% (FFNN), ISIC 2018: 90%, PH2: 95.8% (ResNet-50)	Limited to dataset-specific results and may not generalize to unseen data.
[9]	Acne classification and recommendation of treatments based on classification and severity.	CNN, NLP	Acne Type Classification: 90%-95%, Skin Sensitivity & Acne Density: 93%-96%	High variability in acne types and severity, possibly limiting scalability.
[10]	Detecting and classifying four types of skin diseases (Acne, Keratosis, Eczema Herpeticum, Urticaria).	CNN with 11 layers	Accuracy: 98.6% - 99.04%	Difficulty in generalizing across various skin tones and image acquisition systems.
[11]	Automating the diagnosis and classification of skin diseases.	CNN, Softmax Classifier	Accuracy: 0.87	Limited by the dataset and classifier performance, especially in diverse real-world conditions.
[12]	Skin disease classification using a deep learning model for computational efficiency.	MobileNet V2, LSTM, GLCM	Accuracy: 85%+, faster computation than conventional models	May not perform as well on larger datasets or more complex cases.
[13]	Detection and classification of benign and malignant skin cancer.	LBP, Inception V3, LSTM for feature fusion	Accuracy: 99.4%, Precision: 98.7%, Recall: 98.66%, F-score: 98%	May struggle with complex or unrepresented skin cancer types in the dataset.
[14]	Classifying three skin cancers using EfficientNet models.	EfficientNet-B0 to EfficientNet-B7	Best model (EfficientNet-B4): Accuracy: 79.69%,	Lower performance in some models, and may

			Precision: 81.67%, Recall: 76.56%, F1-score: 79.03%	require more data for better results.
[15]	Diagnosing skin diseases using transfer learning on a novel dataset.	EfficientNet, ResNet, VGG	Best accuracy after augmentation: 87.15%	Accuracy initially low, dependent on dataset quality and augmentation strategies.

Many papers have applied and compared both the state-of-the-art machine learning and deep learning methods to aid dermatologists in achieving reliable diagnoses of skin lesions. In this work [16] deep learning-based CAD systems were employed to investigate the identification of melanoma. The study proposed a new structural architecture through the integration of both Inception v3 and DenseNet models with better accuracy of 91.29% from the ISIC dataset. Likewise, [17] have developed an ensemble learning-based system for the classification of 7 types of skin lesions through deep learning networks, including ResNet, Inception, and hybrid networks. The models were trained using the HAM10000 and ISIC datasets, and data augmentation and class balancing were employed, and the study realized an average validation accuracy of 98.44%'. In [18], there was a transition to the diagnosis of skin diseases using both conventional and deep machine learning methods. At the beginning of the study, the researchers considered a straightforward approach to analyzing the image, with reference to the Histogram of Oriented Gradients (HOG) and Fast Fourier Transform (FFT), followed by the ResNet18, ResNet50, EfficientNet, and InceptionNet images, which revealed to be more accurate and efficient as compared to the previous traditional methods. The work revealed how the integration of deep learning and one of the classical machine learning models could transform the field of dermatological diagnostics. [19] introduced categorization of acne vulgaris into seven types: Inception-ResNet, MobileNet, and EfficientNet pre-trained deep learning models, and the Skin90 dataset. The addition of traditional data augmentation techniques with generative models, such as VAEs, led to better performance on the classification task, with the proposed EfficientNet model showing an accuracy of 89%. The results showed that pre-trained models and generative augmentation types are beneficial but indicated that VAE-augmented data cannot increase performance significantly.

Study [20] recommended integrating deep learning architectures such as DenseNet and InceptionNet with soft attention techniques for heat maps of skin lesions, as well as personal data such as age and gender for classification. The system gained 90% accuracy on the whole HAM10000 dataset, with better-performing and faster MobileNetV3Large as an InceptionResNetV2 real-time diagnosis variant. The study also proposed a new loss function to treat data imbalance and also proved to improve the compound model performance. Last one, [21] proposed the first weighted average ensemble model that incorporated ResNeXt, SeResNeXt, ResNet Xception, and DenseNet for the classification of seven skin lesion types. A grid search approach to model combination and a weighted average ensemble using the rec-weighted method increased recall to 94% compared to individual models and existing systems. As these studies together show, the field has begun shifting toward ensemble learning, deep neural networks, as well as such approaches as soft attention, VAE, and novel loss functions to address the challenges of skin disease classification.

PROPOSED METHODOLOGY

Dataset Description

The dataset for this study comprises 2,357 high-quality dermoscopic images obtained from the International Skin Imaging Collaboration (ISIC), encompassing malignant and benign skin conditions. These images are categorized into eight classes: actinic keratosis, basal cell carcinoma, dermatofibroma, nevus, pigmented benign keratosis, seborrheic keratosis, squamous cell carcinoma, and vascular lesion. The melanoma class was excluded from this dataset due to issues with image quality and inconsistency. Each class is represented in sufficient quantity to facilitate a comprehensive classification task. Unlike previous work, which focused on a binary classification approach involving only two classes, this research addresses the complexity of a multi-class classification problem by

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Research Article

distinguishing between multiple dermatological conditions. Previously, the dataset was not bifurcated into distinct subclasses, limiting the granularity of predictions to merely detecting whether a condition was malignant or benign. In contrast, the current approach adopts a detailed categorization, enabling the model to differentiate between specific skin diseases. This transition from binary to multi-class classification not only enhances the granularity of diagnosis but also provides greater clinical utility, as it can assist dermatologists in identifying specific diseases. The refined bifurcation and inclusion of multiple classes in this study represent a significant advancement in addressing the complex task of skin disease detection, leveraging deep learning techniques to deliver precise and actionable insights.

Data Preprocessing

The data pre-processing of this study entails a number of critical processes to enhance the images and labels required for training the deep learning model. First of all, all images are labelled according to the disease classifications presented in the dataset in order. To standardize the input data, the images are resized to a fixed dimension using OpenCV, which allows uniformity across the dataset and ensures compatibility with the DL model. This resampling procedure operates while preserving the aspect ratio as much as possible to proportionate crucial image features necessary for image classification. Also, the discrete labels for eight skin disease classes are encoded into numerical form by using the LabelBinarizer. This encoding puts the labels into one-hot encoding form, which is desirable for multi-class classification; that way, the model will be able to correctly understand the labels. All of the pre-processing steps together make sure that the data is clean and consistent so that it feeds the deep learning model efficiently. With labelling, resizing, and encoding, the pre-processing step is central to ensuring the subsequent data goes through an accurate and efficient multi-class skin disease detection.

Data Balancing

In this study, the dataset initially showed class imbalance with some categories that were being underrepresented as compared to others. To deal with this problem, the Synthetic Minority Oversampling Technique (SMOTE) was used in order to balance the data. SMOTE synthesizes new samples near the existing ones coming from the minority classes so as to guarantee that all the classes are balanced. This balancing step was important because data may be heavily skewed towards some classes, and this would make the model tend more toward these classes during its prediction. Unlike previous work, in which data balancing techniques were not used, this study uses a more rigorous approach by solving the imbalance problem before training the model. The data was then balanced, and deep learning models were used and further optimized for multiclass classification. Such fine-tuning included changing of the parameters, tweaking of the structure, and using of high-end techniques such as regularization to

increase accuracy and reduce overfitting. When the models were learned through SMOTE to correct for the imbalance issue, the performance improved, and steady accuracy across the classes of the dataset was achieved. This change in the methodological approach for previous investigations underlines the significance of the aspects of data pre-processing and balancing to obtain robust and significant findings in the diagnosed dermatological diseases with the help of deep learning.

Figure 1 is showing architecture diagram of the proposed system which is based on ISIC skin dataset which will go for data preprocessing then data balancing which will balance using the SMOTE technique and so on.

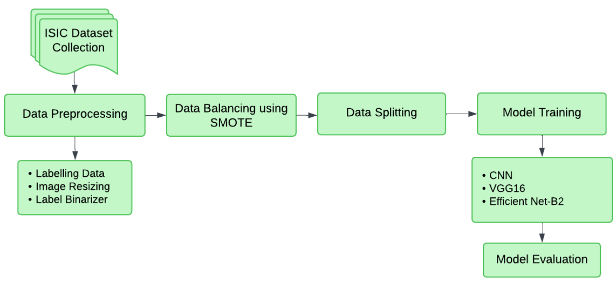

Figure 1: Proposed Workflow Diagram

Journal of Information Systems Engineering and Management
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Research Article

Exploratory Data Analysis (EDA)

The Dermatological Lesion Types Panel shown in Figure 2 consists of eight dermoscopy skin conditions images. The panel is arranged in a 4x2 grid showcasing distinct morphological characteristics of various skin lesions: actinic keratosis characterized by rough, hyperkeratotic, red-brown, scaly plaques with ill-defined margins; basal cell carcinoma presenting as dark brown to black aggregates of chalky white color; dermatofibroma showing central, flesh-toned area with variably pigmented periphery; nevus as sharply defined, brown lesions of uniform color against a blue/gray background; seborrheic keratosis as flattened, well-demarcated, Every picture shows an axes coordinate net in respect to the observed scale; the numbers on the scales mark units from 0 to about 1500. By so doing, the images fulfil their purpose of representing various aspects of standardized patterns of skin lesions as a tool in the differential diagnosis of dermatological clinical pictures.

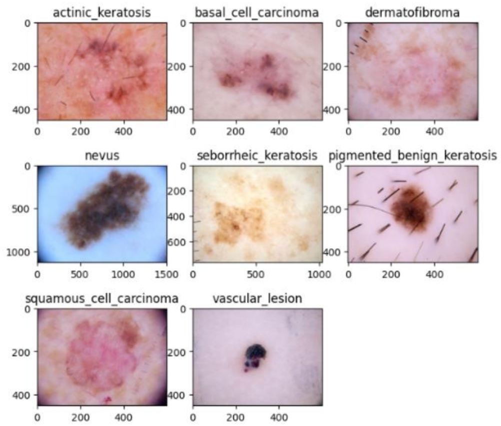

Figure 2: Dermatological Lesion Types Panel

Figure 3, indicating the distribution of skin lesion types before SMOTE application, is a bar chart that describes the class imbalance in the dermatological dataset. The graph describes the eight skin conditions, and the y-axis is the count of samples while the x-axis shows the type of lesions. From the lot, pigmented benign keratosis is the most common with nearly 475 samples, basal cell carcinoma comes close with nearly 390 samples, and nevus had roughly 370 samples. The middle range is dermatofibroma and squamous cell carcinoma, with 110 and 200 samples, respectively. There are a number of less represented conditions, such as actinic keratosis, with about 130 samples; seborrheic keratosis, with around 80 samples; and vascular lesions, with about 140 samples.

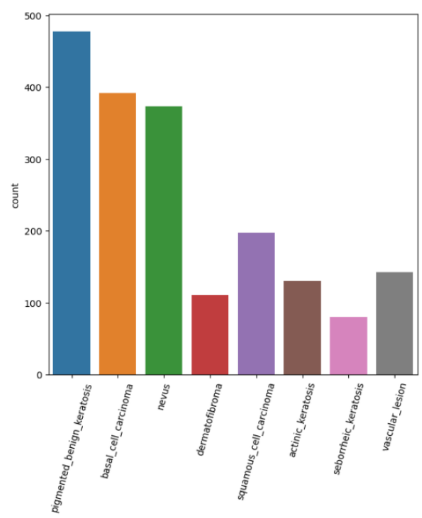

Figure 3: Distribution of Skin Lesion Types Before SMOTE Application

Journal of Information Systems Engineering and Management
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Research Article

Figure 4 gives the distribution of skin lesion types after SMOTE application, revealing a balanced data set after the application of the SMOTE technique. The bar chart clearly shows equal distribution among all the eight dermatological problems, as each one of them now holds almost 475 samples. This balance has been made by synthesizing more samples to the initial dataset for the classes that initially had limited samples; the classes included dermatofibroma, squamous cell carcinoma, actinic keratosis, seborrheic keratosis, and vascular lesion. The y-axis shows the count of samples, while the x-axis lists the different lesion types: pigmented benign keratosis, basal cell skin carcinoma, nevus, dermato fibroma, squamous skin carcinoma, actinic skin keratosis, seborrheic keratosis, and vascular lesion.

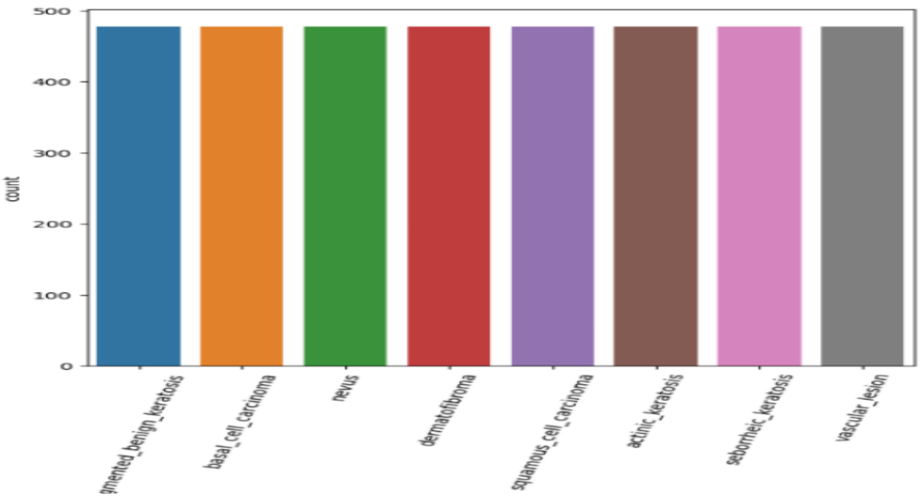

Figure 4: Distribution of Skin Lesion Types After SMOTE Application

Data Splitting

The dataset used in the classification of skin dermatology diseases includes 2,357 images of multi-class diseases obtained from The International Skin Imaging Collaboration (ISIC). These images are categorized into eight distinct classes: The recognition classes include actinic keratosis, basal cell carcinoma, dermatofibroma, nevus, pigmented benign keratosis, seborrheic keratosis, squamous cell carcinoma, and vascular lesion, in which the melanoma class were eliminated because there was missing or distorted illustrations. For robust model training and evaluation, the dataset is split into training and testing subsets using a 90:10 ratio. This is to guarantee that ninety percent of the data will be used to train the model, the other ten percent used to evaluate the model. A stratified division is then made on the train-test split to ensure that each disease type has the same distribution on the testing as well as the training set. It allows the creation of a deep learning model that shall be useful in diagnosing various dermatological complications.

RESULTS AND DISCUSSIONS

CNN Model

CNN is a type of deep learning model [22] that has been designed to process and also analyze visual types of data like video and images [23]. Key components include its layers, like pooling layers, convolutional layers, and all [24].

The confusion matrix of a CNN (Convolutional Neural Network) classification model evaluated over 8 classes (0-7) is depicted in figure 5. The diagonal elements in the muted blue color range between 28 and 47 instances of correct or acceptable predictive model accuracy. The off-diagonal elements of the lighter green represent misclassification, with most values being small (0-9), indicating that there is little confusion between the classes. Some of them are between class 0-1, 0-4, and 1-6, which, although they are relatively few in number, are significant in terms of the number of instances misclassified, where class 0 is misclassified into class 1 (6 instances), misclassifying class 0 into 4 (9 instances), and misclassifying class 1 into 6 (6 instances), respectively.

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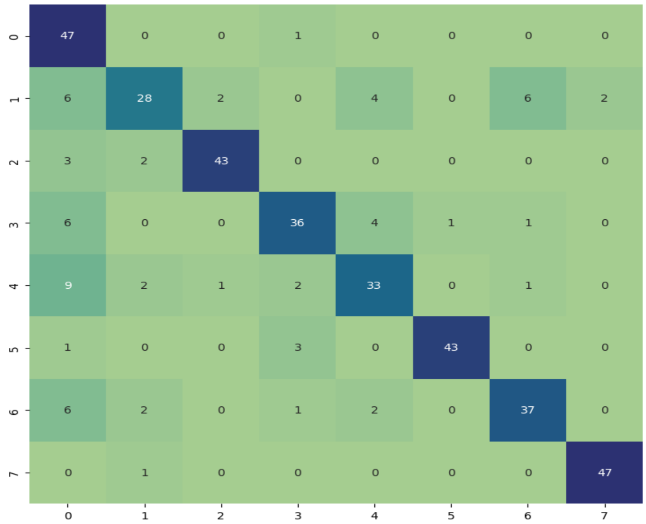

Figure 5: CNN confusion matrix

Figure 6. The performance metrics of a CNN model across 8 different iterations (0-7) demonstrate varying levels of precision, recall, and F1-score. The model shows consistently strong performance, with most metrics above 0.7. Notable peaks occur at iterations 2, 5, and 7, where all three metrics exceed 0.9, indicating optimal model performance. The highest precision (0.98) is achieved at iteration 5, while maximum recall (0.98) occurs at iterations 0 and 7. The F1-score, representing the harmonic mean of precision and recall, reaches its peak (0.97) at iteration 7, suggesting the model's best overall performance at this point.

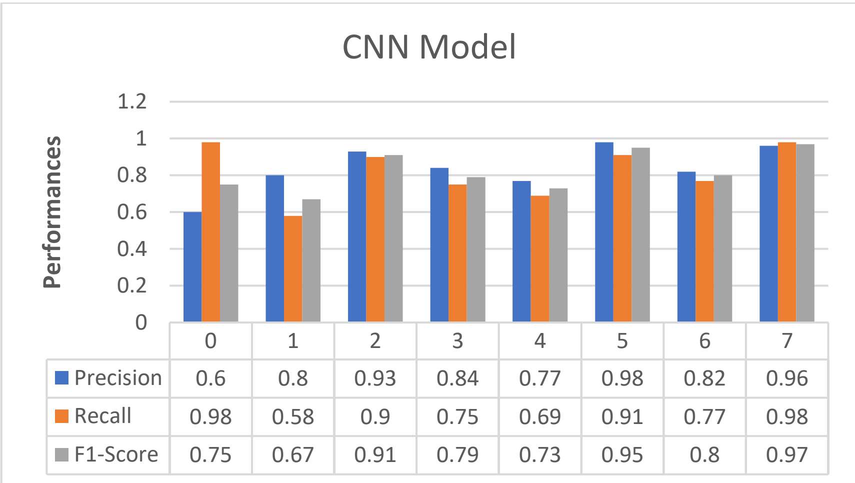

Figure 6: "Performance Metrics Analysis Graph of CNN Model Architecture"

VGG16 Model

VGG16 is a type of deep CNN [25] that was developed by the Visual Geometry Group (VGG) at the University of Oxford [26]. This model has 16 layers, in which 13 are for convolutional layers and 3 are fully connected layers [27].

As shown in figure 7 below, the VGG16 model has produced a confusion matrix of its performance on 8 classes (0-7). The diagonal with darker blue color presentation represents the correct predictions, which vary from 21 to 46 cases. The confusion matrix shows some more serious misclassifications in terms of grouping classes 0-3 and classes 6-4; respectively, there are 18 and 9 instances. Focusing on the evaluation of the model, we can identify its high degree of success for classes 5 and 7, with 44 and 46 correct predictions, correspondingly; however, it demonstrated moderate confusion between the elements of classes 1-4. The off-diagonal, lighter green elements represent a range of misclassification that indicates other areas where the model's discrimination could be gotten right.

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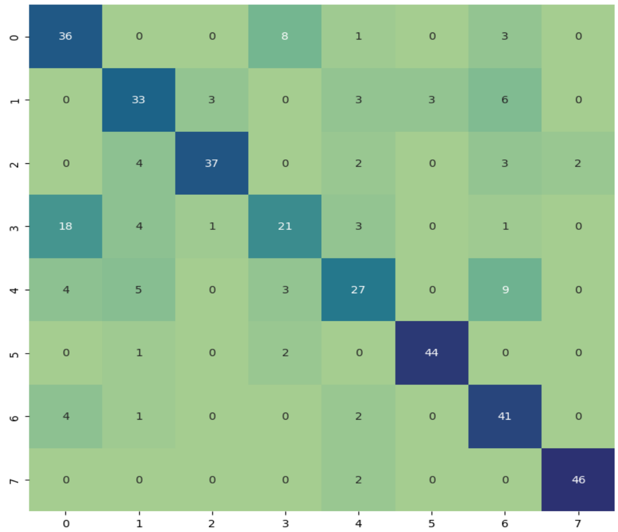
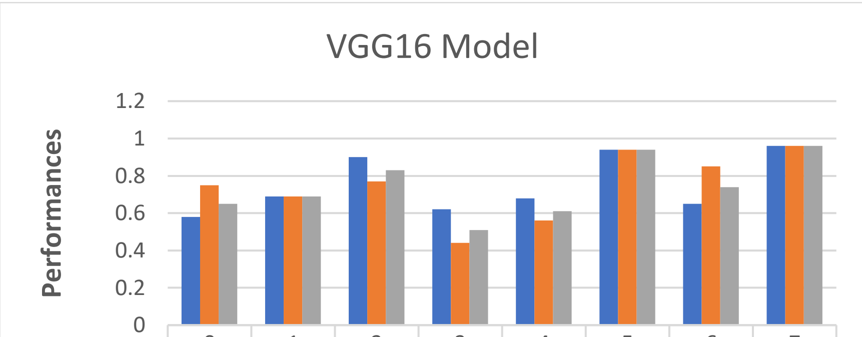


Figure 7: VGG16 confusion matrix

Figure 8 shows a bar chart that is having the performance metrics of the VGG16 model across 8 iterations (0-7) visualized through a grouped bar chart showing precision, recall, and F1-score values. The model exhibits fluctuating performance, with significant improvements at iterations 2, 5, and 7. The highest collective performance is achieved at iterations 5 and 7, where all metrics reach approximately 0.94 and 0.96, respectively. Notable dips occur at iteration 3, where recall drops to 0.44 and F1-score to 0.51, while the model demonstrates consistent improvement in later iterations, culminating in optimal performance at iteration 7.



	0	1	2	3	4	5	6	7
Precision	0.58	0.69	0.9	0.62	0.68	0.94	0.65	0.96
Recall	0.75	0.69	0.77	0.44	0.56	0.94	0.85	0.96
F1-Score	0.65	0.69	0.83	0.51	0.61	0.94	0.74	0.96

Figure 8: "Performance Metrics Analysis Graph of VGG16 Model Architecture"

Efficient Net-B2 Model

EfficientNet-B2 is one of the variants of the EfficientNet model, which is a family of CNNs [28]. It was introduced by Google researchers in 2019 [29]. It adjusts 3 types of dimensions like depth, width, and resolution [30].

Figure 9 is showing a confusion matrix of classification outcomes of an EfficientNet-B2 model in 8 classes (0–7). Dark blue diagonal means that the model has successfully predicted, and there are 25-47 instances, with the greatest performance on classes 5 and 7 with 46 and 47 correct predictions, respectively. The lighter green on the lower left to higher right diagonals represents some misclassifications, chiefly the 14 misclassifications between classes 0-4 and some lesser misclassifications between classes 0-3 and 6-4. In general, the use of the given model shows reasonable classification capacity with only a few accrued massive misclassifications.

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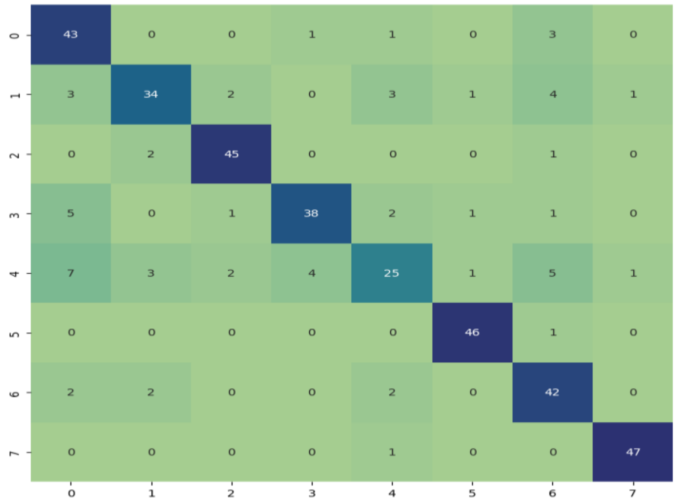

Figure 9: Efficient Net-B2 confusion matrix

Figure 10 is showing the performance evaluation of the Efficient Net-B2 Model which is depicted across 8 iterations (0-7), displaying three key metrics through a grouped bar visualization. The model demonstrates strong overall performance with notable peaks at iterations 5 and 7, where all metrics exceed 0.95. The recall shows the highest variability, dropping significantly to 0.52 at iteration 4 but recovering to reach 0.98 at iterations 5 and 7. The precision maintains relative stability throughout, ranging from 0.72 to 0.96, while the F1-score closely follows the trends of both metrics, achieving its maximum of 0.97 at iteration 7.

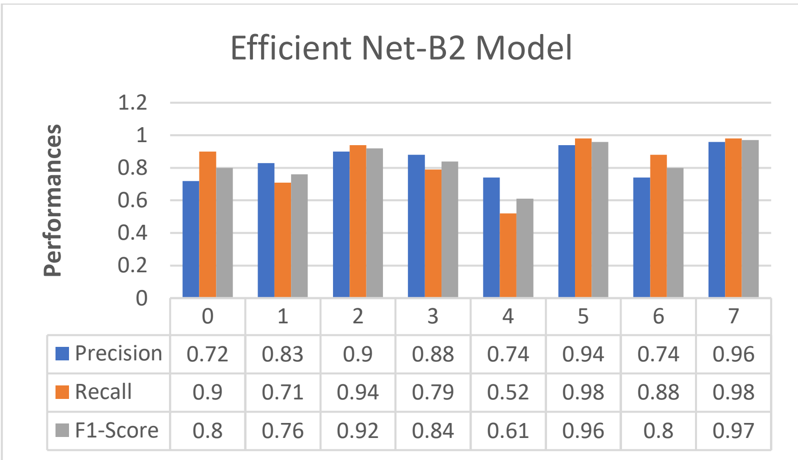

Figure 10: "Performance Metrics Analysis Graph of EfficientNet-B2 Model Architecture"

Table 2: Accuracy Comparison of Different Deep Learning Models

Model	Accuracy (%)
CNN	82
VGG16	74
EfficientNet-B2	84

The study was organized in a good way to handle the intricate task of identifying skin dermatology diseases using deep learning models and made a good advancement as far as data pre-processing, balancing, and fine-tuning phases are concerned. To help the models learn across all eight classes, SMOTE was used to balance the dataset, which had a class imbalance at the beginning of the assessment process. When applied to appropriate models, including the CNN, VGG16, and EfficientNet-B2, the variation assessments showed that the applied models' efficiency in achieving the highest reliable accuracy of 84% out of the given images. This shows the possibility that existed within advanced architectures for the improvement of diagnostic accuracy. Nevertheless, there is even much more to be done. As part of our future endeavour, it will be interesting to augment one or more such novel state-of-the-art deep learning models to achieve better classification performance. There are many other models which can be considered, but for medical image analysis, DenseNet or Xception will be relevant because of their high efficiency. In addition, we are going to add an attention mechanism into the models to enhance the concentration of the features within the images and potentially increase performance. Module that the self-attention or spatial attention will allow the model to focus on the areas of lesions or patterns relevant for diagnosis, which will improve the interpretability and performance in general. Furthermore, attempts will be made to expand the database and add cases with greater differences and variations so that the model may be more effective in true clinical practice. Further work will be done to optimize hyperparameters and try complex forms of data augmentation to decrease overfitting. Finally, the proposed methods will be tested and compared on external datasets to ascertain the suitability, applicability, and robustness of the made model in different clinical settings. The extension of these ideas with more models and attention mechanisms and the enhancement of the quality and variety of the used datasets is this holistic approach, which, in its turn, will contribute to the development of the disease detection field, specifically in dermatology, and will help improve its implementation in practice.

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