Comparative Analysis of the CNN Algorithms for Skin Disease Recognition

Priyanka Ranganath Anarase
Dept. of Electronics & Telecommunications Engineering (VLSI & Embedded System)
Shardchandra Pawar college of Engineering
Otur, India
priyankaanarase49@gmail.com

Dr. G.U. Kharat
Dept. of Electronics & Telecommunications Engineering (VLSI & Embedded System)
Shardchandra Pawar college of Engineering
Otur, India
gukharat@gmail.com

Prof. R. S. Bansode
Dept. of Electronics & Telecommunications Engineering (VLSI & Embedded System)
Shardchandra Pawar college of Engineering
Otur, India
rahulbansodespcoe@gmail.com

***Abstract*— Skin illnesses are found in millions of individuals globally and are problematic because their visibility varies and they require specialist diagnosis. Clinician-performed diagnostic evaluation is subjective, time-consuming, and based on dermatologic expertise, which is sometimes in short supply. This article discusses the application of Convolutional Neural Networks (CNNs) for their potential to diagnose skin conditions with deep learning. Basic CNN and VGG16 are compared on the ISIC skin disease dataset, whose images belong to diverse conditions like melanoma, actinic keratosis, and squamous cell carcinoma. Data augmentation and normalization are used to preprocess the data to make the model generalizable. Precision, recall, F1-score, and accuracy are used for training and testing the models. Experimental results show that VGG16 is the best among others with the highest classification accuracy since it has the best feature propagation and the least computational redundancy. The research presents each model's plus and minus points, depending on their applicability in real-world dermatology applications. Automated classification of skin diseases by CNN-based models can be used as decision-support tools for physicians, allowing early diagnosis and timely intervention. This article contributes to the increasing literature on AI-based medical diagnosis and presents new findings on the best model selection for dermatological disease detection. Future research will continue to enhance model performance for mobile apps, introduce higher levels of interpretability, and provide real-time assistance for clinical decision support.**

Keywords*— *Skin Disease Classification, Deep Learning, Convolutional Neural Networks (CNN), VGG16, ISIC Dataset.

I. Introduction

Skin disease is among the most prevalent worldwide, cutting across ages and populations. It can be as harmless as eczema and acne or as dangerous and life-threatening as melanoma. Accurate and prompt skin disease diagnosis is crucial so appropriate treatment can be given and complications can be prevented. Yet, traditional diagnosis relies primarily on subjective visual assessments by dermatologists, which is time-consuming, subjective, and doctor-dependent. The increase in the incidence of skin diseases and the lack of trained dermatologists, particularly in rural and backward regions, reveal the urgent need for automated, rapid, and reliable diagnostic systems.

As the age of artificial intelligence (AI) and deep learning has come, computerized diagnostic systems are now dynamic means of medical image analysis. CNN, one of the forms of deep comprehension, has had the tremendous capability of doing image classification and thus gained the status as a proper medical diagnosis tool, including the medical diagnosis of skin disorders. CNNs can learn to recognize features of images and patterns that would be hard to notice by the naked eye. They can be taught on vast databases of images of skin conditions so that they will learn to distinguish between different ones accurately, with less need for human knowledge and fewer diagnosis errors.

Using data from the International Skin Imaging Collaboration (ISIC), this research examines and contrasts four CNN architectures Basic CNN, VGG16, and others—to identify skin conditions. One of the standard benchmarks in dermatology literature is the ISIC dataset, which contains high-quality pictures of various skin conditions, including benign and malignant lesions. Comparing the accuracy, precision, recall, and F1 scores of different CNN models is the primary goal of this work to identify the optimal architecture for usage in real-world dermatological application scenarios. Identifying skin diseases is complicated by several factors, including the disease's varying appearance, class-to-class resemblance, and image acquisition conditions. Due to the subjective nature of visual inspection, manual classification is laborious and prone to mistakes. Additionally, the majority of people.

Deep learning has substantially contributed to medical image analysis under the guise of CNNs by providing automated and efficient disease identification techniques. Unlike traditional image processing techniques that entail manual feature extraction, CNNs can learn and extract informative patterns from raw picture data. It is thus ideal to employ highly well in challenging image classification problems, like the discrimination between different skin diseases. Deep models such as VGG16 can learn hierarchical meaningful features. The ISIC dataset is the most excellent resource for deep learning model training because it contains diverse photos of skin diseases. The dataset consists of some skin diseases such as melanoma, squamous cell carcinoma, and actinic keratosis and can be utilized for multiple and natural testing of CNN-based classification models. Based on this dataset, the work employs a rigorous process involving data preprocessing, training of the model, testing for performance, and comparative study. Preprocessing processes of image normalization, resizing, and augmentation are done to provide high-quality normalized input data that is to be learned by the models. The models are trained using supervised learning, wherein images with labels control the network such that disease-specific features are understood. Although deep learning has some capability in diagnosing a medical condition, there are also some limitations in skin disease classification. Data imbalance is typical in that there are some classes of skin diseases with few examples compared to others, and thus, biased predictions by the models are made. Skin diseases have some standard visual features; therefore, models struggle to distinguish classes. Image acquisition inconsistencies in orientation, resolution, and lighting make classification even more challenging. Overfitting plagues it, so models overlearn training sets but cannot generalize to new environments. Overcoming these problems requires robust preprocessing techniques, the construction of balanced datasets, and careful choice of models. This study compares VGG16 and CNN's performance using the ISIC skin disease dataset and relative efficiency determined by the primary evaluation criteria. The study also attempts to determine each model's weak and strong points to identify whether they are viable for use in healthcare environments. The rigorous examination will enable the choice of a diagnostically accurate model and retain computational efficiency for potential use in clinical environments.

This work's contribution is to use deep learning to improve the diagnosis of skin diseases. This paper helps develop AI-powered diagnosis systems to help dermatologists diagnose diseases early by determining the best CNN model. The systems can boost the accuracy of the diagnosis, alleviate the workload from medical professionals, and provide real-time diagnostic support in regions with an underserved specialist healthcare system. AI integration into dermatology can revolutionize the healthcare landscape through efficient and trustworthy solutions for skin disease classification. Classification of skin disease using deep learning is a young field with significant potential to be used in medical diagnosis. This paper compares various CNNs' architectures, their performance, and the most suitable for real-time implementation. With developments in deep learning and AI, auto-diagnosing skin disease can reduce the gap between medical expertise and patient care to increase access to healthcare and render it more efficient. This research result will contribute significantly to AI-based diagnostic solution development that will achieve improved diagnostic results, early skin disease diagnosis, and thus optimal treatment results, as well as patient care.

This paper has the following organization: Chapter 2 is a literature review, summarizing existing research on skin disease classification based on deep learning and identifying research gaps. Chapter 3 is the proposed methodology, outlining data preprocessing, model structures, training protocols, and evaluation measures. Chapter 4 is the implementation, outlining software and hardware requirements utilized in the study. Chapter 5 contains results and discussion, comparing the performances of various CNN models and checking their appropriateness for classifying skin disease. Lastly, Chapter 6 includes a conclusion and future scope, summarizing the main findings and indicating future directions in AI-aided dermatology.

II. LITERATURE SURVEY

Dorj et al. [1] used an online dataset of 3753 images in four classes. They achieved an incredible accuracy of 94.2 percent with an ECOC SVM for classification and AlexNet for feature extraction. Surprisingly, the online-collected dataset did not follow benchmark best practices. Rezvantalab et al. [2] followed a different approach, and the HAM10000 dataset had 120 images distributed across eight classes. Their proposed model, DenseNet 201, showed 86.59 percent accuracy. The authors have used pre-trained models DenseNet 201, ResNet 152, InceptionV3, and InceptionResNetV2. For each of the eight classes, the results have been displayed using AUC measurements ranging from 93.80 percent to 99.3 percent. Hosny et al. [3] used the modified AlexNet to attain an excellent 98.61 percent accuracy, focusing on the PH2 dataset with three classes. The 4400 images generated by the augmentation of the original dataset were obtained using a rescaled AlexNet. The ISIC 2017 data set, which included 5161 photos divided into two groups, produced an AUC value of 81.40 percent, according to Dascalu and David's work [4]. Their novel method looks into how image quality affects diagnostic performance using sonification and K-means clustering.

In another research, Pham et al. [5] used the ISIC 2016 database with 172 images and the HAM10000 database with 1,113 photos of the same class of melanoma skin cancer. Their approach, combining linear normalization, HSV color features, and Local Binary Pattern (LBP) with a balanced random forest classifier, recorded an accuracy of 74.75%. Their primary goal was to compare melanoma cells' color, texture, and shape features. On the other hand, Hekler et al. [6] integrated expert dermatologist ratings with CNN predictions, achieving 82.95% accuracy with the HAM10000 and ISIC datasets (11,444 images), using the XGBoost algorithm for binary and multi-class classification.

Using a pre-modified InceptionV4 model, Emara et al. [7] obtained a 94.7 percent curacy rate when addressing the HAM10000 dataset (7 classes). Their research aimed to propose a pre-modified version of the InceptionV4 model specifically tailored to deal with the imbalanced ratios of the HAM10000 dataset. Using a MobileNet pre-trained model, Chaturvedi et al. [8] achieved 83.1 percent accuracy on the HAM10000 dataset (7 classes). The training was performed on a larger dataset of 38,569 images for the research.

Mohapatra et al. [9] used an unrestrained pre-trained MobileNet on the HAM10000 dataset of seven different classes of skin ailments. They achieved an 80% accuracy rate in their approach, which speaks volumes of the capability of MobileNet for multi-class dermatology image classification. Chen et al. [10] utilized another set of nine diverse classes of skin lesions along with a pre-trained ResNet50 in testing classification performance in another research study. Their method yielded a higher accuracy of 83.74%, focusing on the efficacy of ResNet50 in capturing deep features with high-level features and diversity in skin lesions. Moreover, they also applied the same nine-class dataset to an unchecked pre-trained MobileNet model, which successfully functioned with 80% accuracy. Such results justify the use of deep and light models in real-time for automatically labeling skin diseases.

Jinnai et al. [11] conducted a detailed analysis of the National Cancer Center, Tokyo dataset of 5,846 dermoscopic images distributed over six classes. Their study compared the performance of three models, FRCNN, BCD, and TRN, and provided accuracies of 86.2%, 79.5%, and 75.1%, respectively. To further verify their analysis, they even implemented these classifiers on yet another local dataset divided into two predominant classes of skin cancers: benign and malignant. In yet another significant research work, Chaturvedi et al. [12] analyzed the HAM10000 dataset containing seven classes of images of skin disease. They have achieved an improved accuracy of 92.83% by applying the ResNetXt101 architecture. Their results confirmed the efficiency of ResNetXt101 for histopathological image classification in diagnosing skin disease by being better than other models through strict hyperparameter optimization.

The most dangerous of cancers is skin cancer. It develops when DNA in skin cells gets damaged and not fixed. Damage creates mutations in the skin. Many things can make these; excessive and unguarded sun exposure is the most prevalent and toxic. Skin cancer is also caused if one has a nonhealing sore or if one gets exposed to poisonous chemicals. Nevertheless, more cases are being reported across all age groups. The fastest-growing group to have skin cancer is people aged between 15 and 29 years. Because such problems are severe, many scholars have devised a variety of ways to identify skin cancer at an early stage. Such ways concentrate on the look of lesions—two aspects against the standard and each other (sym-me try, for instance), or colors against size or shapes against finding skin cancer. Some experts even feel free to foretell and sentence who shall conquer whom in the ring of good against melanoma. These efforts rarely come to fruition as effective programming for detecting early skin cancer; however, most programs utilize human visual experts to analyze septal (sandwich) views of a histological section [13].

Dermoscopy is a noninvasive method for diagnosing skin cancer; it is not without drawbacks. Artificial intelligence (AI) is now a vital component of disease detection in most sectors after making enormous strides in recent years. By resolving some of the issues with the traditional method, AI-based automated detection systems in biomedical engineering can potentially improve the accuracy of skin cancer diagnosis. This paper covers an automatic technique for early skin cancer detection. It deals with artificial intelligence and dermoscopic images of skin lesions. The system is segmented using the region-growing and adaptive snake approaches. According to test results, adaptive snakes outperform increasing regions in accuracy and efficiency. SVM and artificial neural networks are The ANN algorithm is 94% accurate, precise at 96%, specific at 95.83%, sensitive (also recall) at 92.30%, and has an F1 score of 0.94. The system is not difficult to implement, consumes a moderate period, and has adequate efficiency to immediately provide patients with the" skin cancer promptly or not" statement [14]. Existing techniques are primarily based on trained human observers in good light. These techniques do and will fail and have potentially lethal effects. We are now in a position that permits and requires a visual inspection approach to skin cancer diagnosis assisted by deep learning. This paper reviews the state of the art regarding such approaches. [15]

Skin cancer is the most prevalent human cancer. Although most are nonmelanoma cancers like squamous cell carcinoma (SCC) and basal cell carcinoma (BCC), melanoma is the most virulent and lethal form. Melanomas are notorious for their rapid color change and may appear on normal skin or within existing moles. Reduction of the occurrences of melanoma and other skin cancer-related complications and fatalities is highly dependent on early and correct diagnosis. CNNs proved to be highly effective aids in allowing visual inspection of skin lesions so that they may be classified correctly based on their potential malignancy [16].

This research has created a new way of identifying early skin cancer. Its foundation lies in the processing of dermoscopic images. It uses an existing convolutional neural network (CNN)-based structure known as the VGG-16 network. Nevertheless, instead of using the standard configuration of the VGG-16 network, we chose a superior version of the network to use as our model's central architecture. As we shall outline, the improvements are primarily in changes to the model's method to process image data. Naturally, we intend to move the accuracy of skin cancer detection toward the point at which it is operationally viable in the real world. According to the results, the suggested model is more precise than the other methods evaluated [17].

In light of this background, ML has recently surged in popularity.ML means DNNs these days, and DNNs are nearly the best thing you can apply with ML to fix a common problem, such as computer vision, speech recognition, or something like assistance with your health. DNNs are deterministic beasts. They function. But you can't possibly know how confident to be in their work without some confidence. You can either guess from an old distribution (which is Bayesian), or you can do lots of "forward passes" of your DNN and then use those to estimate an idea of confidence (which is what MC dropout does). MC doesn't function quite well, though, and that's likely why you could say this paper is inspired. This paper explains how to apply the MCD algorithm in a novel fashion that allows one to construct a deep neural network (DNN) with an internal perception of uncertainty. We demonstrate how this new kind of DNN, an uncertainty-aware DNN, can predict a problem's output and the output's "calibration," i.e., inform us to what degree of confidence or not it is with the work that it just accomplished. Notably, we design our DNN to produce a high predictive entropy for any given instance for which it has made a mistake in the prediction. That is, it can indicate that it is making an educated guess. We experiment with our method on various datasets, synthetic and real-world. Our approach results in state-of-the-art accuracy and credibility of the uncertainty estimation [18].

This study uses a dynamic graph cut algorithm to segment skin lesions and accurately improve skin cancer classification. The proposed model correctly segments skin lesions, even small ones, addressing the frequent over-segmentation and under-segmentation found in cut algorithms. We also illustrate the utility of data augmentation, with our training achieving a top-notch performance metric of 97.986% across six classes in a recent skin cancer contest, mainly because our model yielded many fewer false positives than the next best contestant. Finally, the results of multiple experiments using two different transferring models reveal that the achieved performance is mainly due to errors our model avoided, not because our model suffers from using fresh training images [19].

Although much progress has been made in classifying skin diseases using deep learning, there remain certain gaps in the research that persist. While most work has focused on achieving high accuracy, class imbalance, overfitting, and generalizability to different skin tones and imaging conditions are not addressed. Most models are trained and tested on small datasets, making them less applicable in real clinical practice. In addition, the lack of interpretability of deep learning models is a concern for clinical adoption because clinical users require interpretable and transparent decision-making tools. Few research studies examine lightweight models optimized for running on mobile or embedded platforms, and these models are critical to point-of-care diagnosis in remote or resource-constrained settings. More critically, multimodal data fusion, such as patient history, genetics, and lesion images, is poorly researched.

III. METHODOLOGY

The Block diagram of the proposed system for classification of Skin cancer is shown in Fig. 1.

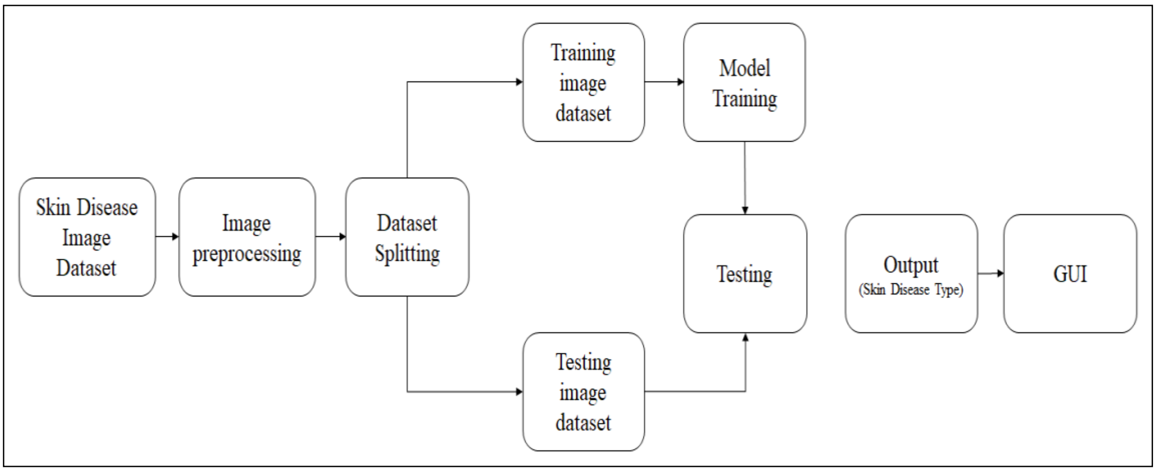

Fig. 1. FigBlock Diagram of the proposed system

A. Image Acquisition

Images with high-quality dermatoscopy from different skin lesions must be acquired to develop and validate deep-learning models. One of the biggest datasets applied across dermatology in this paper is the HAM10000. Dermatofibroma, melanoma, basal cell carcinoma, actinic keratosis, vascular lesions, melanocytic nevi, and benign keratosis-like lesions (the seven subtypes of frequent benign disorders) comprise 10,015 dermatoscopic photos of pigmented skin lesions. The dataset's photos are gathered from many sources to offer variations in lesions' light, texture, and look. They have been professionally captured from environments of hospitals and dermatology clinics and labeled by skilled dermatologists to supply valid classifications. The dataset is well-suited to deep learning because it supplies a sufficient, well-distributed representation of skin disease in the variability of lesion morphology, age, and skin type. Image acquisition is crucial in automatic skin disease classification because it determines the model's generalizability across various real-world environments.

B. Image Preprocessing

Image pre-processing is preparing the raw images to be fed into the models. Pre-processing the image involves resizing images into a standard width and height, normalizing (scaling pixel values between 0 and 1), and data augmentation (rotation, flipping, or brightness adjustment). Data augmentation strengthens the models because it artificially replicates real-world situations under which leaves or light may be oriented in some other way. Preprocessing removes noise and normalizes input data to allow the model to concentrate on significant disease features rather than redundant variations

C. Training and classification

The model is trained with multiple forward and backward passes during training time using texture, color, and boundary features of lesions trained across convolutional layers. Additionally, the model is regularized, and data augmentation techniques, including rotation, flip, contrast stretching, and normalization, prevent overfitting. To improve convergence and guarantee learning stability, we normalize the Basic CNN and VGG16 models using the Adam optimizer, batch normalization, and categorical cross-entropy loss. Contrasting models compare overall classification performance with the baseline performance metrics of accuracy, precision, recall, and F1-score.

Based on patterns discovered during training, the trained model uses an input image of a skin lesion to categorize it into one of the seven groups. The output layer's softmax activation function assigns a probability score to each class after making the final classification decision based on patterns that have been learned. The model selects the class with the highest probability as the diagnosis. Due to its sound feature propagation and reduced computational redundancy, Vgg16 outperforms the other studied architectures, yielding the highest classification accuracy. In dermatology, the trained model can serve as a helpful decision-support tool that aids medical professionals in accurately and consistently diagnosing skin conditions.

IV. RESULTS AND DISCUSSION

The experimental findings of this study provide a comprehensive assessment of the efficacy of several CNN architectures for classifying skin disorders using the HAM10000 dataset. The models were trained and evaluated using accuracy, precision, recall, and F1-score to ensure the practical classification assessment. In this section, the findings of VGG16 and Basic CNN are compared. The following is the deep learning algorithm's output. Table I shows how well different deep-learning algorithms classify skin diseases.

TABLE I. PERFORMANCE OF DEEP LEARNING ALGORITHM FOR SKIN DISEASE RECOGNITION

Classifier	***Training Accuracy (%)***	***Validation Accuracy (%)***
CNN	69.53	69.33
Vgg16	71.85	71.13

The performance of the VGG16 deep learning model versus a basic CNN model in classifying skin diseases using the HAM10000 dataset is contrasted in Table I. Regarding training and validation accuracy, VGG16 performs better than a basic CNN. For instance, a basic CNN model demonstrated moderate learning but low generalization abilities, training with 69.53 percent accuracy and validating with 69.33 percent accuracy. On the other hand, VGG16 was trained to 71.85% and tested to 71.13%, clearly showing improved feature extraction and generalization to unseen data. This is because VGG16 is a deeper model and can learn more intricate patterns and hierarchical features to discriminate between disparate skin conditions. The comparatively small difference in training and validation accuracy between the two models is similar to minimal overfitting. Overall, the result points to VGG16 as a functioning classifier for classifying skin diseases, hence the right one for practical dermatological diagnostics.

V. Conclusion and Future Scope

To address the problems associated with manual diagnosis, this study investigated using CNN in the computerized classification of skin diseases. As the prevalence of skin conditions rose and the demand for reliable and efficient diagnostic tools grew, deep learning-based models emerged. Basic CNN and VGG16 were compared with the ISIC dataset. VGG16 was the best-performing model relative to other architectures because it had the highest accuracy, precision, recall, and F1 score and, thus, the best model to bet on in derm applications. The paper suggests future AI-based dermatology diagnostic platforms to improve clinical practitioners' decision-making. Despite model performance challenges, including data unbalance, intra-class similarities, and image acquisition heterogeneity. Overfitting and computational complexity are problems, particularly model deployment on mobile and embedded devices. Despite these problems, the work lays a good foundation for CNN-based skin disease classification and illuminates model selection for AI-aided dermatology.

Technological advancements in AI-based diagnostics and deep learning continually unveil new possibilities for more accurate skin disease classification. The future hinges on merging AI with IoT devices and real-time tracking systems to ensure immediate diagnoses and increased accessibility to remote populations. The dataset must be more significant because it includes diverging skin conditions from different groups to generalize models and stem the tide of bias. Optimization of CNN architectures for mobile and edge devices is another critical area, allowing real-time diagnosis using lightweight deep learning models without compromising accuracy.

In addition, incorporating Explainable AI (XAI) techniques such as Grad-CAM and SHAP visualizations will provide additional interpretability to models, making AI-based skin disease classification more transparent and reliable for clinicians. Hybrid models combining CNN transformer-based models and multi-modality inputs like dermoscopy images and patient history can further improve diagnostic accuracy. Image quality, lighting, and angle variations will be handled through more advanced data augmentation and domain adaptation techniques, increasing model robustness. The model validation through clinical collaboration with dermatologists and the development of diagnostic user-friendly apps will propel real-world deployment. With the ongoing evolution of healthcare through AI, multi-modal AI systems integrating medical imaging with genetic, environmental, and patient history data will transform detection for skin disease and render diagnosis more accurate, efficient, and accessible globally for healthcare applications.

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