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Skin Disease Classification using CNN Deep Learning Technique

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ABSTRACT

Skin diseases rank among the most prevalent health conditions globally, yet their diagnosis remains challenging, primarily due to the intricate interplay of factors such as skin tone, color variations, and hair presence. The diverse manifestations, initial symptom similarities, and uneven distribution of lesion samples further compound the complexity of accurately classifying these disorders. Deep Convolutional Neural Networks (CNNs) have exhibited remarkable potential in improving the precision of skin disease classification. This paper presents a novel approach that involves developing a custom-built CNN architecture from scratch to classify skin diseases with high accuracy. Unlike existing models that rely on pre-trained architectures, our model is designed and trained from the ground up, tailored specifically to the unique characteristics of dermatological image data. The architecture comprises multiple convolutional and pooling layers, followed by dense layers with Batch Normalization and ReLU activation to ensure effective learning and generalization. Comprehensive experiments were conducted to evaluate the performance of the proposed CNN model. Results demonstrate that the model achieves a notable accuracy rate of 84.9%, along with a competitive F1-score, confirming its reliability in practical applications. Despite the absence of transfer learning or pre-trained weights, the proposed model effectively captures discriminative features necessary for skin disease classification.

General Terms Image processing, Custom-built CNN model, ReLU and SELU activation functions, Eczema, Melanocytic Nevi, Melanoma Basal Cell Carcinoma, Benign Keratosis Lesions, Atopic Dermatitis Deep Learning techniques, state-of-the-art model, Dermatological image classification, Convolutional Neural Networks (CNNs), Batch Normalization.

Keywords: Skin disease images, Custom CNN model, Deep learning, OpenCV, Image classification, Convolutional Neural Networks (CNN), Batch Normalization, ReLU, SELU.

1. Introduction

The most delicate and important human body organ is skin that protects us against diseases, heat and damage. Unfortunately bacterial and viral infections, fungus, a lack immune system and genetic imbalances can occasionally affect the skin's state. Diseases caused by those variables frequently have gruesome impacts on human existence. Additionally some skin conditions are infectious, putting not only the affected person but also others close to them at danger. Skin diseases are not well known to most people. Occasionally, those diseases don't do too much harm. They may result in serious health problems. Therefore, it is essential to understand their consequences. A number of laboratory pathology tests are used in the diagnosis of skin diseases in order to identify the correct illness. Over the past 10 years, these diseases have been a source of concern due to their rapid appearance and complexity, which also increase the risks associated with living. Due to their high contagiousness, these skin defects must be treated quickly to stop them from spreading. Overall well-being is adversely impacted, which includes mental and physical welfare as well as personal welfare. Many of these skin abnormalities are

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quite fatal, especially if left untreated at an early stage. Skin disorders range widely in terms of severity and range of symptoms. They could be either long-term or short-term, painless or excruciating. Certain ones are inherited, while others are influenced by current event. Skin issues can be either non-threatening or potentially fatal. While most skin issues are rather minor, some may indicate a more serious condition. Prejudice affects medical experts' evaluations in a similar way that each human search begins with the terms selected by the user. When a doctor makes an assumption diagnosis, they usually look for evidence to support their theories before ruling out other possible diseases until their theories are proven false. The order or weight allocated to any of the symptoms would probably bias the findings towards a correct diagnosis, even if another sign is overlooked and not included in the search or taken into immediate consideration. Early control of the illness is essential if it is to be stopped from spreading. Skin conditions can negatively impact a person's mental health as well as their self-esteem in addition to their skin's look. Skin conditions are now a prominent cause of public concern as a result. Early detection and timely treatment of several skin problems are essential to preventing lasting skin damage.

2. Review of Literature

This research work focuses on the development of a robust model for skin disease classification using a custom deep learning architecture built entirely from scratch, rather than relying on pre-trained models such as Xception. Various researchers have employed different machine learning and deep learning techniques for the classification of skin diseases. Rifat *et al.* (2023) suggested an efficient solution for skin disease recognition by implementing Convolutional Neural Network (CNN) architectures, MobileNet, and Xception, deep learning techniques were utilized to construct an expert system that could accurately and efficiently recognize different classes of skin diseases and achieved classifications accuracy of 96.00% with MobileNet and 97.00% with Xception model. Padmavathi *et al.* (2020) proposed computer-aided techniques in deep learning neural networks such as Convolutional neural networks (CNN) and Residual Neural Networks (ResNet) to predict skin diseases in real-time and they got an accuracy 77% and 68% with CNN and ResNet respectively. Malliga *et al.* (2020) developed a model that has an ability to recognize and classify the skin diseases. They demonstrated how the model performance may be enhanced by a reasonable network structure. The authors proposed CNN algorithm with 938 skin images that are Melanoma, nevi, and seborrheic keratosis and achieved 71% of accuracy. They have also tried AlexNet model, which gave better accuracy as 76.1%.

Chaturvedi *et al.* (2020) suggested deep learning methods CNN and ResNet classification algorithm for an automated computer-aided diagnosis system for multi-class skin (MCS) cancer classification with an exceptionally high accuracy. They performed fine-tuning over seven classes of HAM10000 dataset with five pre-trained convolutional neural networks (CNNs) and four ensemble models, where suggested algorithm given 93.20% of accuracy for single model and 92.83% with an ensemble model. Ahmed *et al.* (2018) developed an automated framework that efficiently performs a reliable automatic lesion classification for dermatology and that follows an ensemble approach by combining ResNet-50 and Inception V3 architectures to classify the seven different skin disease types. The overall accuracy achieved by proposed algorithm is 89.90%.

In paper Sasiakala *et al.,* (2022) the authors combined Convolutional Neural Network with three predefined models called Alex Net, ResNet, InceptionV3 classifier. The experiment done with a skin disease dataset consists of 7000 images with seven skin diseases. Velasco *et al.* (2019) developed a MobileNet model by applying CNN transfer learning methods with 7 skin diseases and created a skin disease classification system on Android application. The author gathered 3,406 skin disease images from online public access dermatology repositories. They used oversampling technique and data augmentation on preprocessing the input data and they got 84.28% accuracy.

Xinrong and Firoozeh (2022) presented a method for diagnosis of skin cancer from dermoscopy images. The Proposed Xception method was then implemented to MNIST skin cancer dataset, which utilized swish activation function and depth wise separable convolutions. The system showed an improvement in the classification accuracy of the network compared to the original Xception and other architectures. Rahman and Am, (2020) used three state of-the-art deep learning pre-trained models for classification of the skin lesions like ResNet, Xception and DenseNet., They used the HAM10000 dataset for the purpose of training and evaluation of models and obtained balanced accuracy of 78%, 82%, and 82% for ResNet, Xception and DenseNet models respectively. Then they combined the three models using the weighted ensemble technique without any further training and the overall accuracy achieved got 85.8% balanced accuracy.

Patnaik *et al.* (2018) suggested Deep learning algorithms like Inception v3, Inception V2, and MobileNet for feature extraction and classification. They further combined the Inception V3, MobileNet, Inception V2 and created ensemble models for classification of dermatology. The proposed Inception V3 model achieved better accuracy 88.28% as compared to Inception V2 and MobileNet. Mehmood *et al.* (2023) used Xception as the base model for skin cancer classification and increases its performance by reducing the depth and expanding the breadth of the Xception architecture. They used the HAM10000 dataset, which contains 10,015 images of skin dermatology and classified into seven categories. Gupta *et al.* (2022) proposed Xception model that included one pooling layer, two dense layers, and a dropout layer for the purpose of modified architecture of Xception model. This experiment used HAM10000 skin disease dataset with seven classes for skin diseases. The dataset imbalance was fixed by using data augmentation techniques. The updated model has a classification accuracy of 96.40% for skin disorders.

Purnomo and Palupi, (2021) have used Xception, Inception V3, Seresnext101, ResNet50, DenseNet121, GoogleNetand EfficientNet techniques for classification skin diseases. The evaluation results of each model were compared, and then the best results were selected which determines the best model. Kethana and Mohamed, (2022) developed CNN model with the help of feature extraction that reduced the need for human labor, such as manual feature extraction and data reconstruction for classification of skin disease. A dataset consists of 10015 skin disease images that include Nevus, Melanoma, and Sebborheic Keratosis and achieved 92% accuracy. In paper (Wei *et al.,* 2023) the author proposed a fusion model by using convolutional neural network algorithm for skin disease classification with public HAM10000 skin disease dataset. Pre-training, data augmentation, and parameter fine-tuning were conducted to enhance the performance of model. The proposed model created the two baseline models of DenseNet201 and ConvNeXt_L. and fine-tuning of both the model where DenseNet201 and ConvNeXt_L got 95.29% accuracy and 89.99% respectively. Naga *et al.* (2021) have used convolutional neural networks, a technique based on transfer learning, to present a multiclass skin disease classification model. The results of the pre-trained models like VGG16, VGG19, ResNet50, ResNet101, ResNet152, and Xception MobileNet compared in terms of accuracy.

Velasco *et al.,* (2023) developed a system including VGG16, VGG19, MobileNet, ResNet50, InceptionV3, Inception- ResNetV2, Xception, DenseNet121, DenseNet169, DenseNet201, and NASNet mobile to classify skin diseases with transfer learning approaches. The MobileNet based model achieved best accuracy as 94.1%. Maduranga and Nandasena, (2022) used CNN-based technique for identifying and classification of skin disease. MobileNet with transfer learning method got a best model for automatic skin disease identification on a Smartphone and achieved accuracy of 85%. In paper (Kong and Cheng, 2021) the author created a model incorporating convolutional neural networks with long short-term memory (LSTM) classifiers. The author optimizes the problem and achieving a 99% overall accuracy rate by combining Pearson feature selection concepts and the fusing of the correlation between the two loss functions to achieve automatic pneumonia detection in X-ray pictures. In (Gada *et al.,* 2022) fully connected Convolutional networks like InceptionV3 and XgBoost classifiers are used to predict seven classes based on 74 features and 4,200 images.

Raza *et al.* (2022) proposed model by using the ideas of transfer learning and fine-tuning the stacked ensemble method for melanoma classificatio, including Xception, Inceptionv3, InceptionResNet-V2, DenseNet121, and DenseNet201. This methodology performed better than state of-the-art methods.

Moataz *et al.* (2021) investigated a model by adding a group of layers after the Xception model for classification of skin lesions. A seven-class augmentation strategy is used to fine-tune the model over the HAM10,000 dataset in order to reduce the effect of data imbalance. Using a balanced dataset, the proposed model performance achieved 96% accuracy. Panthakkan *et al.* (2022) introduced a Deep learning CNN model for classification of skin disease with HAM10000 dataset. They have also propsed X-R50 model and compared with CNN model and got 97.8% of accuracy. Srinivasu *et al.* (2021) designed computerised model employing MobileNet V2 and Long Short Term Memory (LSTM) was developed for the classification of skin diseases. A grey-level co-occurrence matrix is utilized to evaluate the progression of the disease development and the effectiveness of the system has been evaluated in comparison to other Fine- Tune models such as the Visual Geometry Group (VGG) Fine Tuned Neural Networks (FTNN), Convolutional Neural Networks (CNN), and Very Deep

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Convolutional Networks for Large-Scale Image Recognition. Azeem *et al.* (2024) investigated the detection of melanoma using different deep learning technaiues using augmented HAM 10,000 dataset and achieved accuracy 84% by AlexNet model. The other models achieved accuracies 89% and 90% with VGGNet 19 and VGGNet 16 respectively. The highest accuracy achieved 92% with ResNet50 while 90% with Xception model.

3. Proposed Methodology

3.1. Custom-Built Deep Learning Model for Multi-Class Skin Disease Classification

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 224, 224, 32)	896
batch_normalization (BatchNormalization)	(None, 224, 224, 32)	128
max_pooling2d (MaxPooling2D)	(None, 112, 112, 32)	0
dropout (Dropout)	(None, 112, 112, 32)	0
conv2d_1 (Conv2D)	(None, 112, 112, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 112, 112, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 56, 56, 64)	0
dropout_1 (Dropout)	(None, 56, 56, 64)	0
conv2d_2 (Conv2D)	(None, 56, 56, 128)	73,856
batch_normalization_2 (BatchNormalization)	(None, 56, 56, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 28, 28, 128)	0
dropout_2 (Dropout)	(None, 28, 28, 128)	0
flatten (Flatten)	(None, 100352)	0
dense (Dense)	(None, 256)	25,690,368
dropout_3 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32,896
dropout_4 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 6)	774

Total params: 25,818,182 (98.49 MB)

Trainable params: 25,817,734 (98.49 MB)

Non-trainable params: 448 (1.75 KB)

Fig 1: CNN model architecture

In the context of the Convolutional Neural Network (CNN) architecture presented, the process unfolds as follows:

First, RGB input images are resized to a standardized resolution of 224 × 224 pixels. The model begins with the conv2d layer, which extracts initial low-level features using 32 filters, producing feature maps of size 224×224×32. distinguishing source code text. If Times Roman is not available, try the font named Computer Modern Roman. On a Macintosh, use the font named Times. Right margins should be justified, not ragged.

This is followed by a batch_normalization layer that accelerates training and improves stability by normalizing activations. A max pooling2d layer then reduces the spatial dimensions to 112×112×32, decreasing computational complexity while preserving important features.

To mitigate overfitting, a dropout layer is applied, randomly deactivating a portion of the neurons during training.

The model deepens with conv2d_1, which uses 64 filters to produce feature maps of size 112×112×64, followed by batch_normalization_1, max_pooling2d_1 to reduce the dimensions to 56×56×64, and another dropout_1 layer.

The next layer, conv2d_2, further increases the feature depth using 128 filters, generating feature maps of size 56×56×128. After passing through batch_normalization_2 and max_pooling2d_2, the feature maps are down sampled to 28×28×128, followed by dropout_2.

A flatten layer then reshapes the 3D feature maps into a 1D vector of 109,352 units, preparing the data for the fully connected layers.

The first dense layer (dense) consists of 256 units, serving as a high-level feature integrator. A dropout_3 layer follows to prevent overfitting.

Next is dense_1 with 128 units, which further refines the feature representation. After another dropout layer (dropout_4), the model ends with dense_2, a final classification layer with 6 output units, likely using softmax activation to classify input images into one of six categories.

For optimization, the model employs the Adam adaptive optimizer with a learning rate of 0.0001, and uses Categorical Crossentropy as the loss function suitable for multi-class classification problems where the labels are one-hot encoded. The model's performance is evaluated using accuracy as the primary metric.

To enhance training efficiency and prevent overfitting, two key callbacks are integrated:

- Early stopping is configured to monitor the validation loss (val loss). Training is halted if no improvement is observed over 10 consecutive epochs, and the best-performing model weights are automatically restored
- Reduce LROn Plateau dynamically adjusts the learning rate by reducing it by a factor of 0.5 if the validation loss stagnates for 3 epochs, with a minimum learning rate threshold set to 1e-6.

The fine-tuning process is conducted over a span of 34 epochs, enabling the model to gradually converge while maintaining generalization on unseen data.

In terms of parameterization, the model encompasses a total of 25,818,182 parameters, equivalent to roughly 98.49 MB of memory usage. Of these, 25,817,734 parameters (98.49 MB) are designated as trainable, while the remaining 448 parameters (1.75 KB) are marked as non-trainable. Non-trainable parameters primarily arise from layers such as Batch Normalization, which store statistics rather than learnable weights. This comprehensive architecture and parameterization strategy allow the convolutional neural network (CNN) to effectively classify input images into the specified categories while optimizing for both performance and memory efficiency.

4. Dataset Description and Augmentation

Skin disease image dataset collected from the Kaggle data science, Dermnet and ISCI website Kethana and Mohamed, (2022), which comprises a total of 19,457 images categorized into four distinct classes: Eczema, Melanocytic Nevi, Melanoma Basal Cell Carcinoma, Benign Keratosis Lesions and Atopic Dermatitis. It is important to note that the entire dataset was utilized for both training and validation purposes, with an 80% allocation for training and the remaining 20% for validation (Patnaik *et al.,* 2018). These images, as found in the Kaggle dataset, are represented in the RGB color space. Although they originally exhibit pixel values within the [0, 255] range, a critical preprocessing step was applied to normalize the RGB values, thereby transforming them into the interval [-1, 1].

Furthermore, the dermoscopic images in the dataset were uniformly resized to dimensions of 224 x 224 x 32 pixels, ensuring consistent input size across all layers of the model. Subsequently, the dataset was partitioned into two subsets: 16572 images designated for training and 2885 images reserved for validation purposes. Table 1 shows the description of dataset with training, validation and testing samples with four different classes and Figure 3 shows the sample training dataset of skin disease images.

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Table 1: Dataset classes

Classes	No. of Images for Training	No. of Images for validation	No. of Images for test
Atopic Dermatitis	1068	160	160
Basal Cell Carcinoma	3323	498	549
Eczema	1677	251	254
Melanoma	3136	470	471
Benign Keratosis Lesions	2079	313	312
Melanocytic Nevi	5579	1195	1196

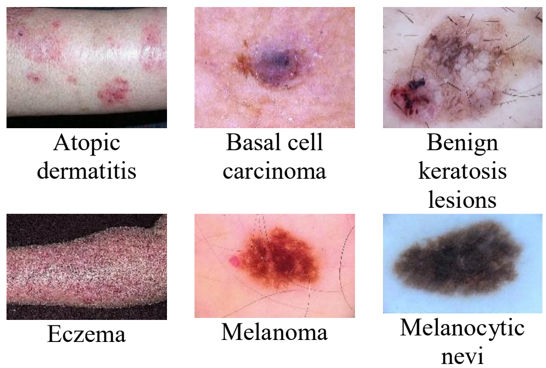

Fig 3: Sample of training dataset with skin disease images

5. Experimental Work Setup

The proposed model was trained and evaluated on a computing platform with the following specifications: a Dell G15 laptop equipped with an Intel Core i7 processor, 16 GB of RAM, and an NVIDIA GeForce RTX 3050 GPU. This hardware configuration was carefully selected to meet the computational demands of training a deep neural network. The implementation was carried out using the Python programming language. For deep learning tasks, the Keras framework integrated with TensorFlow was used as the primary development environment. All experiments and computations were executed within a Jupyter Notebook environment (Gupta *et al.,* 2022).

5.1. Experimental Results

The CNN model was rigorously assessed using a distinct set of 2885photographs that were excluded from the original training dataset of 16572 images across four classes. Additionally, a separate set of 96 photos was reserved for comprehensive testing. As illustrated in Figure 4, the CNN model demonstrated strong performance, achieving a training accuracy of 84% and a validation accuracy of 83%. Figure 4 displays the training and validation accuracy and loss graphs.

An 'Early Stopping' callback has been incorporated into the model to mitigate overfitting during the training process. This callback is configured to continuously monitor the validation loss during training and will terminate training if the validation loss fails to show improvement for three consecutive epochs, effectively preventing excessive overfitting. Furthermore, to be considered a significant improvement, the validation loss must exhibit a minimum change of 0.01; changes below this threshold are deemed insignificant and do not trigger the early stopping mechanism.

Fig 5: Confusion matrix of CNN model

6. Conclusion

A custom-built Convolutional Neural Network (CNN) model for the classification of skin diseases is presented in this paper. Unlike pre-trained architectures, the proposed model was constructed from scratch and trained entirely on a labeled dataset of skin disease images to achieve high classification accuracy. A comprehensive hyper parameter tuning process was conducted to determine the optimal configuration. Experimental results demonstrate the model's effectiveness in accurately categorizing various skin diseases. The proposed model's performance was rigorously evaluated using a balanced dataset, achieving an impressive accuracy rate of 84%. This performance level positions it competitively among recent state-of-the-art models in the field. In future, we will use different deep learning based models with optimization techniques and preprocessing techniques to enhance the quality of images and improve the performance of the model.

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