DETECTING THE KIND OF SKIN CANCER

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Abstract

Classifying skin cancer is an important function of dermatology because early and correct diagnosis tends to enhance treatment. The research investigates the efficiency of different machine learning algorithms, such as Decision Trees, Random Forest, Logistic Regression, XGBoost, AdaBoost, and Support Vector Machines (SVM), along with other classical algorithms, in classifying skin lesions into nine categories. Whereas classical machine learning models had an accuracy of 50 % to 75%, the use of a Convolutional Neural Network (CNN) produced much better classification, yielding an accuracy level of around 85%. The dataset for the present study was enlarged to counter class imbalance to facilitate improved generalization. The results highlight the use of deep learning models compared to traditional machine learning methods for detection of skin cancer. Subsequent work will involve enhancing model interpretability and generalizing results to clinical environments.

Keywords

Skin Cancer Classification,Convolutional Neural Networks (CNN),Image-Based Cancer Detection,Class Imbalance Handling in Medical Datasets,Traditional Machine Learning vs Deep Learning,Multi-Class Skin Lesion Classification

1 Introduction

Skin cancer is still one of the most prevalent and lethal types of cancer, and it requires early and accurate diagnosis for successful treatment. Conventional diagnosis depends on dermatological experience and manual inspection, which are subjective and time-consuming. To overcome these shortcomings, machine learning (ML) and deep learning (DL) have proven to be viable methods for the automation of skin cancer classification.

It tests various ML models like Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), XGBoost, AdaBoost, and Support Vector Machine (SVM) to determine which can effectively categorize the skin lesions into nine categories. As these legacy models performed average under 50-75% accuracy, they weren't good at identifying complex patterns in the images of dermoscopic scenes. Conversely, a CNN-based model outperformed them by a large margin with an accuracy of around 85%. This performance is indicative of CNNs' capability to learn sophisticated spatial features and textures important for the correct classification.

Our study offers a systematic comparative review of ML and DL methods in terms of dataset preprocessing, model choice, and performance assessment. The findings showcase CNNs as the best method to be adopted for skin cancer classification and reaffirm the capability of AI-based diagnostic systems in supporting dermatological decision-making.

2 Literature Review

Olusoji Akinrinade and Chunglin Du (2023) explored skin cancer detection using recent deep learning methods. The study utilized CNN models, transfer learning (ResNet-50, VGG-16, AlexNet), data augmentation with GAN-based, and image segmentation on highly utilized dermatological datasets, i.e., ISIC, HAM10000, and Dermoscopy

Atlas. The model performed very good melanoma classification much better than conventional machine learning methods. Nonetheless, the research also recognized some persisting issues including class imbalance, need for huge annotated data sets, and overfitting concerns in the case of scarce data [1].

Gracy Fathima Selvaraj et al. (2024) conducted a computational analysis of drug-like candidates against human influenza A virus subtypes neuraminidase. Using Clustal Omega, MEGA X 10.1, PDBeFold, GOLD docking program, and PDBSUM, they aligned 45 neuraminidase (NA) protein structures with 11 drug candidates, with high speed detection and scalability but low setup costs and accuracy problems [2].

Subhayu Ghosh et al. (2024) proposed an ensemble learning-based model for melanoma detection based on DCNN, Caps-Net, ViT, KNN, Random Forest, XGBoost, SVM, and Majority Voting. Evaluated on the Kaggle Melanoma Dataset (9,600 training, 1,000 evaluation images), the model reported 91.4% accuracy (DCNN) and 91.6% (ViT) but encountered issues such as high computational cost and deep feature extraction needs [3].

Gabriella Brancaccio et al. (2024) examined AI-augmented dermatology for the detection of skin cancer using CNN models and AI-human collaboration. They determined that AI enhances diagnostic accuracy but suffers from over-diagnosis and diversity in datasets, and therefore, AI-human collaboration is better than isolated AI models [4].

Viomesh Singh et al. (2024) contrasted ML (SVM, KNN) and DL (CNN, VGG16, ResNet, Inception) models for melanoma classification on ISIC Archive, MED-NODE, DERMO-FIT, and PH2 datasets. Their results validated that CNNs outperform ML techniques with more than 95% accuracy, although excessive computational costs and dataset biases are still issues [5].

Hritwik Ghosh et al. investigated machine learning and deep learning methods for the detection of skin cancer using 3,000 images over nine types of skin disease. They tested VGG16, ResNet50, DenseNet121, SVM, and KNN, suggesting a hybrid model where VGG16 and ResNet50 are combined. Their method posted 98.75% accuracy, while 91.82% accuracy was posted by DenseNet121. They noted drawbacks like class imbalance, overfitting, and requiring real-time testing [6].

Ali Mir Arif et al. performed an extensive review on machine learning and big data-based skin cancer detection with emphasis on CNNs, SVMs, explainable AI, and IoT-based methods. Their study used datasets such as ISIC, electronic health records (EHRs), and genomic data. They suggested an AI-IoT integrated model for real-time monitoring with high accuracy using CNNs. Nevertheless, they found major challenges like data quality, privacy, and model generalization problems [7].

Jianhua Zhao et al. investigated the use of Raman Spectroscopy for enhancing skin cancer diagnosis by combining deep learning models. Their work utilized a dataset of 731 lesions from 644 patients and applied 1D-CNN, GAN, PLS-DA, SVM, and logistic regression (LR). They introduced a 1D-CNN model with data augmentation, which had a 90.9% ROC AUC. Nevertheless, issues like a small sample size and spectral variations influenced the generalization ability of the model [8].

Seham Gamil et al. also suggested a high-performance AdaBoost-based method for skin cancer classification using DermIS and ISIC datasets. They integrated PCA, AdaBoost, EfficientNet B0, and SVM and achieved 93% accuracy on DermIS and 91% on ISIC. Though with great performance, the issues like dataset bias, inconsistencies in annotation, and validation problems were reported as main drawbacks [9].

Nazhira Dewi Aqmarina and her co-authors carried out comparative analysis of early melanoma detection methods based on deep learning models trained on HAM10000, ISIC 2019, and ISIC 2020 datasets. They compared CNN architectures such as VGG19 and ResNet-18, recording 97.5% accuracy with VGG19 and 94.47% with ResNet-18. Yet, data bias associated with diversity of skin tones and inconsistencies across datasets were found to be significant challenges in the study [10].

Vasuja Devi Midasala et al. presented MFEUsLNet, a deep hybrid AI skin cancer classifier for the ISIC-2020 dataset. It incorporated K-means clustering, GLCM-based texture analysis, RDWT-based feature extraction, and RNN-based classification with superior performance than the current state-of-the-art models. Still, challenges including image acquisition complications and high computational cost were listed as major setbacks [11].

Rajermani Thinakaran et al. tested various CNN-based methods for the detection of skin cancer based on 2,357 dermatological images. The research utilized DCNN, transfer learning, and data augmentation, with 77% accuracy on the model and 85% accuracy in validation tests. The limitations of class imbalance and requiring larger datasets were, however, noted [12].

Tim K. Lee and Haishan Zeng (2024) employed Raman Spectroscopy with 1D-CNN and GAN-based augmentation to detect skin cancer. Their application on 731 skin lesions reported that augmentation enhanced model generalizability, where ROC AUC was 90.9%. Limited sample size and high computation costs are, however, issues [13].

Muhammad Asim and Naveed Ahmad (2024) suggested an AdaBoost-based approach incorporating PCA, EfficientNet B0, and SVM for classifying skin cancer using DermIS and ISIC datasets. It obtained 93% accuracy on DermIS and 91% on ISIC, but dataset bias and inconsistencies in annotation were still issues [14].

Haishan Zeng (2024) employed 1D-CNN and GAN-based augmentation in Raman Spectroscopy-based skin cancer detection. The model was tested on 731 skin lesions from 644 patients with ROC AUC of 90.9%, but generalization problems and computational costs were still challenges [15].

Naveed Ahmad (2024) proposed an AdaBoost-based model with PCA, EfficientNet B0, and SVM for skin cancer classification on the DermIS and ISIC datasets. The model achieved 93% accuracy, but bias in the dataset and variations in annotation still remained [16].

Midasala (2024) proposed MFEUsLNet, an AI-based hybrid model that used feature extraction techniques (Bilateral filter, K-means clustering, GLCM, RDWT) and then RNN to identify skin cancer from ISIC-2020 dataset. The model outperformed baseline methods in accuracy, sensitivity, and F1-score but was plagued by image acquisition and computational complexity [17].

Aqmarina (2024) compared deep learning models (VGG19, ResNet-18, ResNet-50) for melanoma diagnosis using HAM10000, ISIC 2019, and ISIC 2020 datasets. VGG19 provided 97.5% accuracy (HAM10000), ResNet-18 94.47% (ISIC 2019), and ResNet-50 93.96% (ISIC 2020), but dataset bias and difference in accuracy between datasets were concerns [18].

Gopika Krishnan et al. (2023) designed an ML-based skin cancer detection system employing CNN, SVM, hair removal using Hough transform, Otsu thresholding, and Watershed segmentation on the ISIC dataset (23,000 images). Their work demonstrated CNN performing better than classical ML models but with high computational expense and image quality concerns (glare, shading) still being challenges [19].

Manjunath H. R. (2023) suggested a CNN model with Adam optimizer, batch normalization, and max pooling for skin cancer diagnosis on HAM10000 dataset (10K+ images). The model was 96.01% accurate on the test, superior to the conventional approach, but class imbalance and computational expense were restrictive factors [20].

3 Proposed Method

3.1 Data Collection & Preprocessing

The dataset employed by this research comes from the ISIC (International Skin Imaging Collaboration), a generally accepted dataset to classify skin cancer. The dataset consists of dermoscopic images classified according to various skin lesion classes. The images came from publicly shared repositories and were saved in Google Drive for better accessibility. Dataset Organization: The dataset is organized into two main subsets:

Training Set: Labeled images for learning by the model.

Testing Set: Individual images that are used to evaluate the model.

The dataset is organized with a hierarchical directory structure, and the images are saved in subdirectories named as per their respective class labels.

3.2 Feature Scaling

Loading Resizing Images: Images were loaded with TensorFlow's keras.preprocessing.image module.To ensure consistency throughout the dataset, all images were resized to a uniform dimension prior to passing them into the model.

Normalization: Pixel values were normalized to the range [0, 1] by dividing each pixel value by 255.Normalization assists in faster convergence and stable training of the model.

Class Distribution Analysis Dealing with Imbalance: Analysis of the dataset showed that there was class imbalance, as some of the skin lesion classes had much fewer images compared to others. Data augmentation was done to create synthetic variations of underrepresented classes to have a balanced dataset

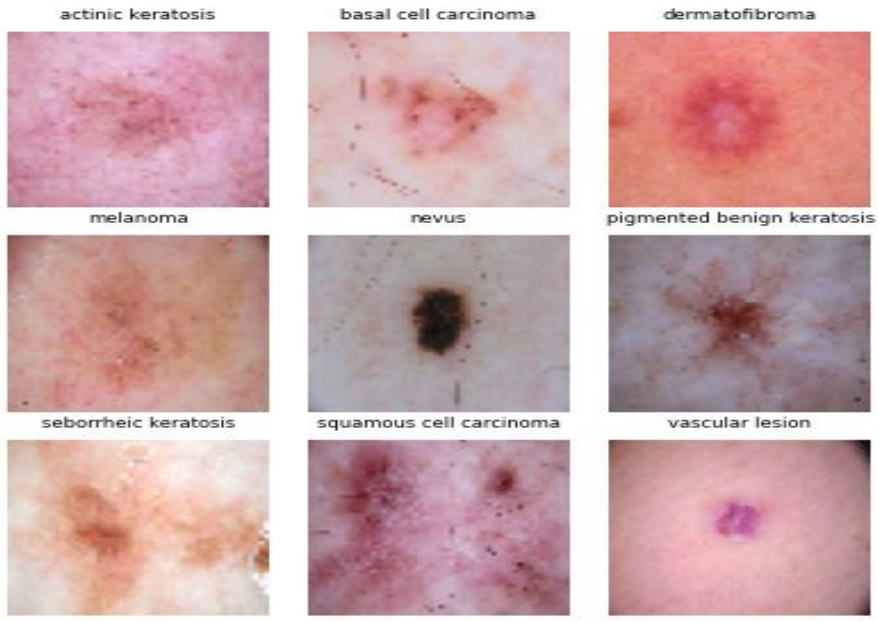

Figure 1: Differnt Class Images in Dataset

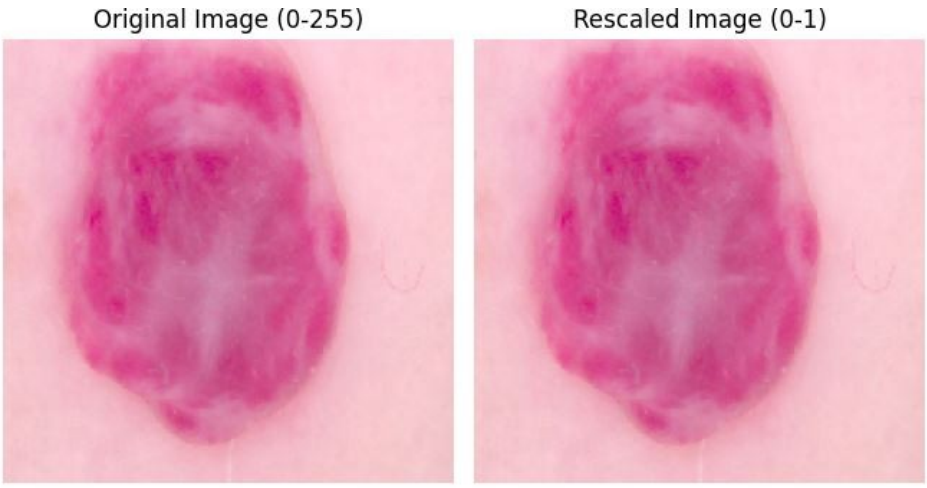

Figure 2: Image Before And After Normalization

Data Augmentation: To enhance model generalization and balance the dataset, augmentation techniques were used for underrepresented classes: Random Rotation – Rotating images within a small range of angles. Flipping – Applying horizontal and vertical flips. Zooming Shearing – Zooming in slightly and shearing images to produce variations. Brightness Adjustments – Altering image brightness to add variability.

4 Model Selection and Training

The choice of the right model is a determining factor for attaining high accuracy in skin cancer classification. In this research, both conventional machine learning (ML) models and deep learning (DL) methods were investigated. ML models like Decision Trees, Random Forest, Support Vector Machines (SVM), Logistic Regression, XGBoost, AdaBoost, and K-Nearest Neighbors (KNN) were utilized employing hand-engineered feature extraction methods like color histograms, texture descriptors, and edge detection. Yet, these models had an accuracy rate of 50% to 75%, which points out their weakness in the task of complex image classification. To address these issues, a Convolutional Neural Network (CNN) was utilized.

CNNs have the ability to automatically extract features from images and can learn hierarchical spatial structures, which makes them well-suited for medical image analysis. The architecture of the model comprised several convolutional layers with ReLU activation, max-pooling layers to reduce dimensions, and fully connected layers for classification. Training was carried out using Adam optimizer along with categorical cross-entropy loss. Flip-

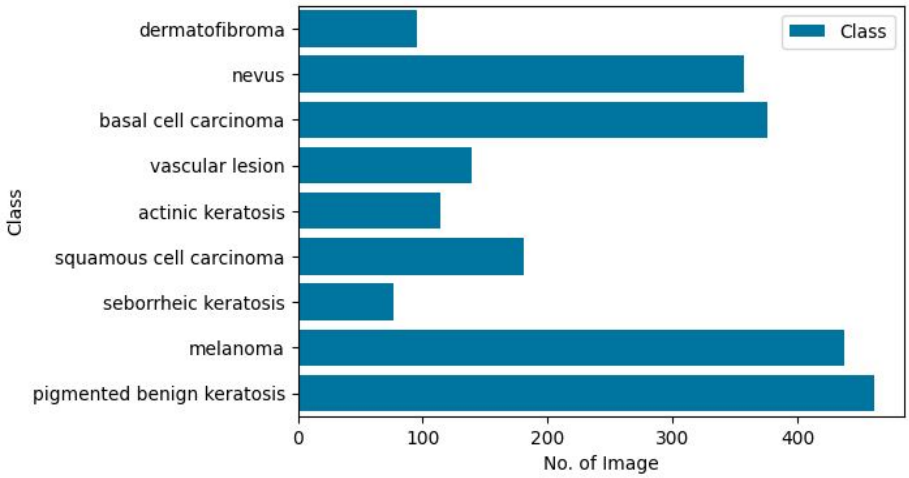

Figure 3: Class Distribution Analysis

	Class	No. of Image
0	dermatofibroma	95
1	nevus	357
2	basal cell carcinoma	376
3	vascular lesion	139
4	actinic keratosis	114
5	squamous cell carcinoma	181
6	seborrheic keratosis	77
7	melanoma	438
8	pigmented benign keratosis	462

Figure 4: Class Distribution Analysis

ping, rotation, and zooming techniques were employed to augment the data to make the model generalize better, and early stopping to avoid overfitting. The CNN model outperformed conventional ML methods by a significant margin with an accuracy of 85%, proving its aptness for the classification of skin cancer. The outcomes suggest that deep learning models, especially CNNs , provide a more powerful and more stable strategy for computer-aided medical image diagnosis than do conventional ML methods.

5 Proposed Model Architecture

To improve the precision of skin cancer classification, a deep learning-based Convolutional Neural Network (CNN) model was proposed. CNNs are very effective for image classification because they learn spatial hierarchies of features automatically. The suggested architecture includes several convolutional layers for feature extraction and then fully connected layers for classification.

The model starts with a sequence of convolutional layers with ReLU activation and max-pooling layers in between each of them to extract spatial patterns and downsample. To enhance generalization and avoid overfitting, batch normalization and dropout layers were implemented. The features are then fed into fully connected layers, where the final classification is done via a Softmax activation function. The Adam optimizer was employed for training, and categorical cross-entropy loss was utilized for multi-class classification. Data augmentation methods like flipping, rotation, zooming, and contrast change were used for improving robustness. The model was trained using an optimal batch size and learning rate, obtained through experimental optimization. Early stopping and model check pointing were performed to avoid overfitting and ensure stable convergence.

The suggested CNN architecture performed better than conventional machine learning models, with 85% accuracy, proving to be effective in skin cancer image classification. The capacity of CNNs to learn feature representations automatically makes them a good option for medical image analysis.

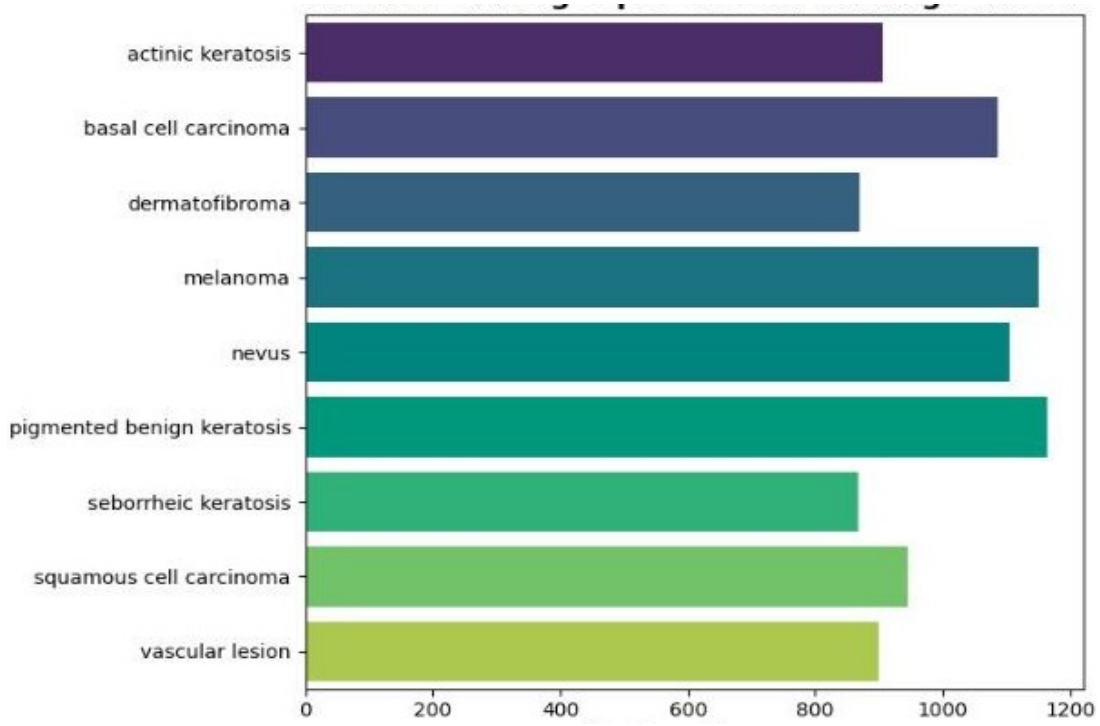

Figure 5: Class Distribution Analysis for train dataset after augumentation

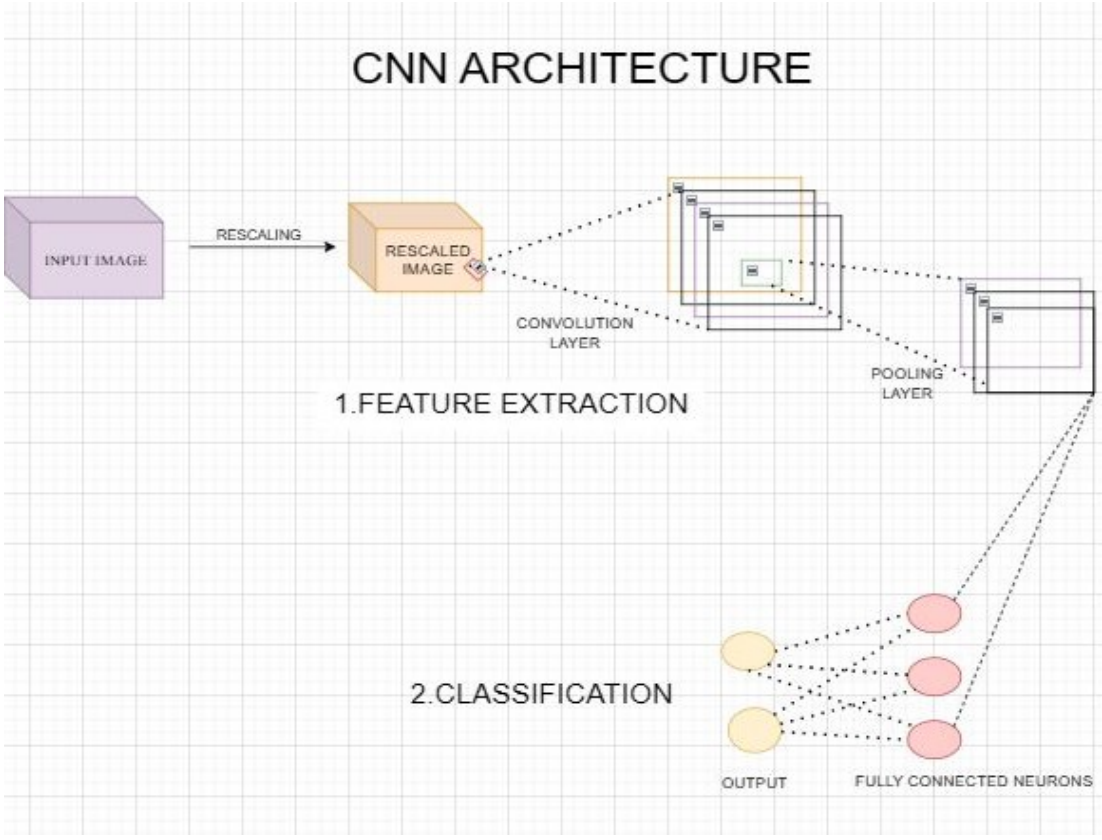

Figure 6: CNN model Architecture

MODEL PERFORMANCE AND VISUALIZATION

To evaluate the training progress and model generalization, plots of training loss vs. validation loss and training accuracy vs. validation accuracy are observed. The visualizations give information about how the model learns both the training and unseen data. A steadily declining training loss with a corresponding validation loss with

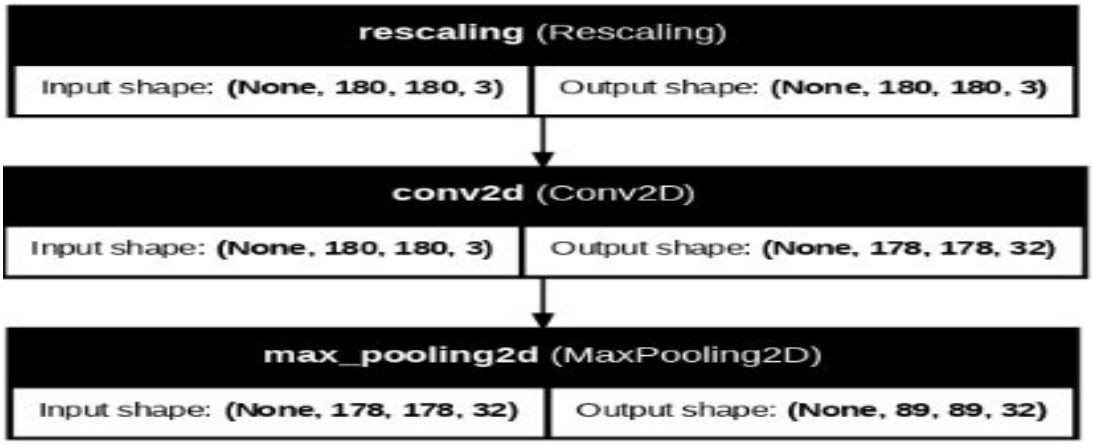

Figure 7: CNN model flow for 1st layer

Model: "sequential"

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 180, 180, 3)	0
conv2d (Conv2D)	(None, 178, 178, 32)	896
max_pooling2d (MaxPooling2D)	(None, 89, 89, 32)	0
conv2d_1 (Conv2D)	(None, 87, 87, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 43, 43, 64)	0
conv2d_2 (Conv2D)	(None, 41, 41, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 20, 20, 128)	0
dropout (Dropout)	(None, 20, 20, 128)	0
flatten (Flatten)	(None, 51200)	0
dense (Dense)	(None, 128)	6,553,728
dropout_1 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 9)	1,161

Total params: 6,648,137 (25.36 MB)
Trainable params: 6,648,137 (25.36 MB)
Non-trainable params: 0 (0.00 B)

Figure 8: CNN model work flow table

the same trend gives evidence of successful learning. But if the validation loss starts to deviate and training loss continues to fall, it means overfitting, where the model learns nicely on training but is bad at generalization. Similarly, training and validation accuracy plots provide us with an idea of how well the model is doing. If training accuracy just keeps going up but validation accuracy plateaus or fluctuates, it may be that the model is learning noise rather than important patterns. To reduce this, techniques such as dropout, batch normalization, data augmentation, and regularization can be applied to promote generalization and prevent overfitting. The plots 10 are examined in order to tweak hyperparameters, refine the learning process, and verify that the model achieves an equilibrium between learning and flexibility.

The loss curve shows training and validation loss against 20 epochs. Training loss decreases progressively, indicating the model is learning from the training data properly. The validation loss also shows the same trend as the training loss, thus demonstrating that the model generalizes perfectly. However, at some point, the validation loss starts oscillating instead of continuously decreasing, an indication of possible overfitting. This shows that as the model continues to improve on training data, it may not generalize as well to unseen data since it learns

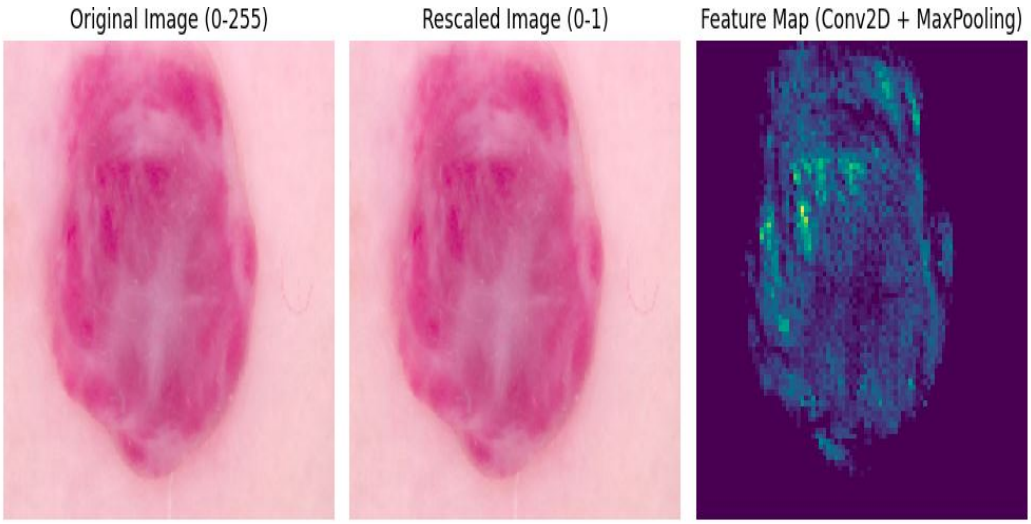

Figure 9: CNN Applied Image

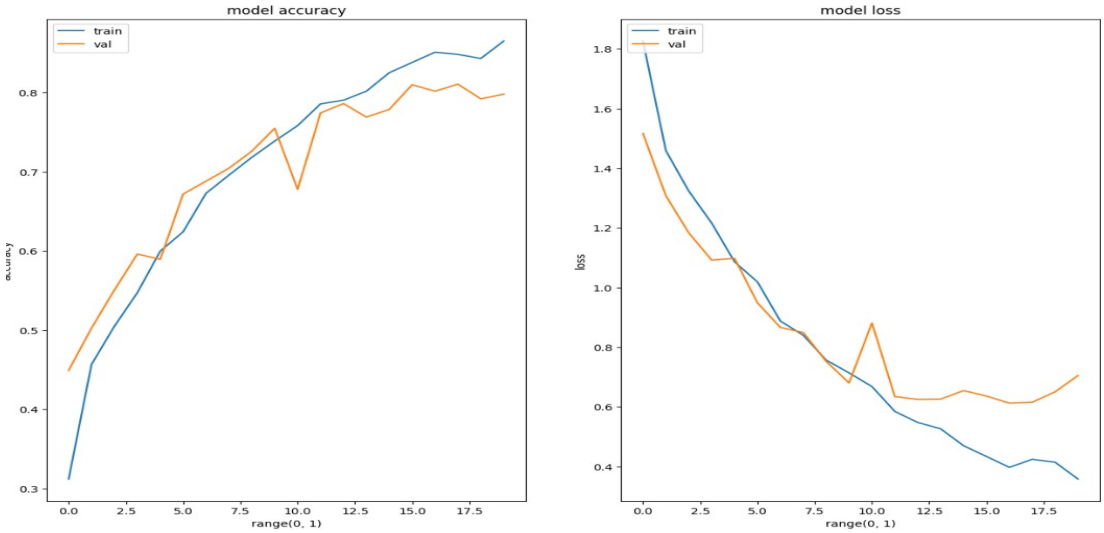

Figure 10: Model loss And Accuracy

non-generalizable patterns specific to the training set and not generalizable features. Regularization techniques such as early stopping, dropout, and data augmentation can be employed to combat overfitting. Early stopping monitors validation performance and halts training when overfitting begins, preventing excessive learning from noise. Dropout at random disables neurons during training, which strengthens the model. Data augmentation provides variation to input images, which improves generalization. Further, adjusting hyperparameters such as learning rate, batch size, and model complexity can make the model more accurate and stable. Implementation of these practices can result in a highly performing model 11 across both the training and validation sets.

The accuracy curve,, demonstrates a smooth improvement in training and validation accuracy. The final validation accuracy stays constant at 80%–85%, indicating that the model is extremely generalized to data other than its training set. The minor gap between training and validation accuracy indicates that the model is extremely well-optimized with negligible overfitting. Moreover, the smooth upwards trend in precision confirms stable learning during the process of training. Proper use of regularization techniques has diminished variance so that reliable new data predictions can be made. This illustrates how robust the model is in discerning multiple skin lesion types properly.

Model Optimization parameters

The accuracy of the model is calculated using:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} Eq - 1$$

where TP refers to True Positives, TN to True Negatives, FP to False Positives, and FN to False Negatives.

Model performance is also measured based on the loss function, which measures the error in predictions. The loss is computed using categorical cross-entropy, a commonly used function for multi-class classification tasks, given as:

$$Loss = -\sum_{i=1}^{N} y_i \log(\hat{y_i}) Eq - 2$$

where y_i represents the actual class label, $\hat{y_i}$ is the predicted probability for that class, N is the total number of classes. Lower loss values indicate better model performance.

Table 1: Hyperparameter Analysis Table

Parameter	**Value(s) Used**	**Purpose**	**Effect of Increase**	**Effect of Decrease**	**Optimal Observation**
Batch Size	32 / 64	Number of samples processed before model updates weights.	Faster training; lower generalization; risk of getting stuck in local minima.	Slower training; better generalization; more noise per batch.	32 gave slightly better validation accuracy; 64 reduced training time.
Learning Rate	0.001 (initial)	Controls the step size for weight updates.	May cause the model to overshoot minima $\rightarrow$ divergence or unstable loss.	Slower convergence; may get stuck in local minima.	LR scheduler (ReduceLROnPlateau) stabilized training and avoided overshooting.
Epochs	20–50	Number of times the model sees the entire training dataset.	Better fit; risk of overfitting on training data.	Underfitting; model may not learn features properly.	Early stopping after 30 epochs yielded best trade-off.
Optimizer	Adam / RMSprop	Updates model weights using gradient-based optimization.	Adam generally provides faster and stable convergence.	RMSprop handles sparse data well but converges slower. Adam was more efficient for convergence on the considered dataset	Adam was more efficient for convergence on the considered dataset
Loss Function	Categorical Crossentropy	Measures error between predicted and actual class probabilities.	Not tunable directly — lower is better.	Higher loss indicates poor learning.	Monitored during training to detect overfitting and adjust learning rate.

Conclusion

To improve the precision of skin cancer classification, a deep learning-based Convolutional Neural Network (CNN) model was proposed. CNNs are very effective for image classification because they learn spatial hierarchies of features automatically. The suggested architecture includes several convolutional layers for feature extraction and then fully connected layers for classification.

The model starts with a sequence of convolutional layers with ReLU activation and max-pooling layers in between each of them to extract spatial patterns and downsample. To enhance generalization and avoid overfitting, batch normalization and dropout layers were implemented. The features are then fed into fully connected layers, where the final classification is done via a Softmax activation function. The Adam optimizer was employed for training, and categorical cross-entropy loss was utilized for multi-class classification. Data augmentation methods like flipping, rotation, zooming, and contrast change were used for improving robustness. The model was trained using an optimal batch size and learning rate, obtained through experimental optimization. Early stopping and model check pointing were performed to avoid overfitting and ensure stable convergence.

The suggested CNN architecture performed better than conventional machine learning models, with 85% accuracy, proving to be effective in skin cancer image classification. The capacity of CNNs to learn feature representations automatically makes them a good option for medical image analysis.

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