DEEP CNN MODEL FOR SKIN LESION CLASSIFICATION AND DETECTION

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Abstract- Skin lesions refer to various abnormal conditions on the skin, like moles, spots, ulcers, and growths. They can occur due to different reasons, such as genetic factors, exposure to the environment, or viral infections. However, telling the difference between harmless lesions and potentially cancerous growths is a difficult job that needs careful examination and expertise. In the past, analyzing skin lesions involved mainly looking at them and interpreting them subjectively. This approach had its limitations, leading to differences in how accurately they were diagnosed and sometimes causing delays in identifying cancerous lesions. Furthermore, we require a more effective and reliable approach to treat the rising number of cases as more people get skin illnesses. The primary objective of this study is to build a deep convolutional neural network (CNN) model that makes use of deep learning techniques' capabilities. The primary objective is to significantly enhance the accuracy of skin lesion analysis. The proposed model uses a big collection of pictures of skin lesions to learn how to tell different types of lesions. By using deep learning algorithms, this model can accurately classify and detect skin lesions. This is really helpful because it allows for early detection and timely medical intervention, which is important for effective treatment.

Keywords– *skin lesion, dataset, image categorization, CNN, dermatological condition, dermatological image processing.*

I.INTRODUCTION

The early diagnosis and treatment of an array of skin problems in dermatology significantly depend on the classification and identification of skin lesions. Deep convolutional neural networks (CNNs) have proven to be incredibly effective at analyzing images of skin lesions, and they are now powerful tools for precise image classification. This work aims to develop a state-of-the-art skin lesion categorization and detection system based on CNN. To do this, 2357 skin lesion photos gathered from credible websites like Kaggle are combined into a complete dataset. To ensure the dataset's quality, consistency, and applicability for training, it is crucial to preprocess it before training the deep CNN model. Data validation, cleaning, augmentation, normalization, picture- resizing, cropping, and dataset splitting are just a few crucial activities that fall under the category of data preparation. These preprocessing methods standardize and optimize the dataset, guaranteeing that the deep CNN model receives consistent and accurate data. As a result, skin lesion categorization and detection are more accurately and consistently performed. This improves the model's capacity to learn from and generalize the training data. Additionally, this research classifies and analyzes data using several deep learning algorithms, including Support Vector Machines (SVM), Decision Trees (DT), Random Forests (RF), Voting Classifier, AlexNet, Inception V3, VGG16, Inception ResNetV2, MobileNet, and Xception. These algorithms aid in the evaluation and comparison of various models and offer perceptions of how well they operate. This work seeks to enhance the area of dermatology by creating new methods for deep learning algorithms and thorough data preparation.

II. LITERATURE REVIEW

F. Santos et al [1] have looked into the use of deep neural networks for the automated diagnosis of skin lesions, focusing on the effectiveness of transfer learning methods for multi-class skin lesion categorization. The International Skin Imaging Collaboration (ISIC) and developments in Convolutional Neural Network designs are important in this article's quest for cutting-edge outcomes. The research's tests show that employing previously trained models can significantly improve deep-learning classifiers' overall performance when it comes to categorizing skin lesions. Additionally, the research stressed the importance of having a high-quality dataset and the advantages of creating class balance through data augmentation approaches.

J. Aguilar et al [2] employed a database of acne sufferers whose chances of getting scars were assessed using the 4-ASRAT, a tool with four questions. They trained for binary and triple classification utilizing a set of data and a specific CNN model architecture. The best binary model demonstrated potential in predicting future acne scars with 93.15%

accuracy, 19.45% loss, and 0.931 AUC. Triple categorization was difficult, which suggests that CNN-based models may be useful for estimating the risk of acne-related scarring using picture analysis.

K. Rezaee et al [3] suggested a bi-directional feature fusion architecture to enhance the classification accuracy of skin lesions by combining the benefits of both Transformer and CNN branches. Furthermore, the bidirectional, dual-branch feature arrangement enhances the model's ability to differentiate various skin lesions.

F. Santos et al. [4] have created a number of strategies to identify out-of-distribution samples while analysing skin lesions. Methods encompass likelihood-based (e.g., maximum softmax probability, entropy), distance-based and density-based (e.g., Gaussian mixture models, kernel density estimation). Studies suggest density-based methods excel in out-of-distribution sample detection.

Mohakud et al [5] conducted research on Automated Hyper-parameter Optimized Convolutional Neural Networks (CNNs) to classify skin cancer. Fine-tuning CNN hyper-parameters are complex and time-consuming. They used the Grey Wolf Optimization algorithm, comparing it to Particle Swarm Optimization and Genetic Algorithm. The model achieved remarkable 98.33% testing accuracy.

Fantini et al [6] have demonstrated a technique to instruct four well-liked designs for fine-tuning, and transfer learning methodologies were utilized to examine 68 T1-weighted volumetric data from healthy individuals.

A. Kumar et al [7] researched the creation and application of a deep learning (DL) model for the automated classification of skin lesions using dermoscopic pictures. To address binary classification limitations in skin cancer screening, researchers introduced a specialized DCNN model, leveraging selected layers and filters. Using ISIC-17, ISIC-18, and ISIC-19 databases, they outperformed existing methods, achieving remarkable results.

M. S. Junayed et al [8] have made a potential development in dermatology by introducing a transformer-based model for automated segmentation and categorization of acne lesions. Machine learning and image processing enhance personalized acne treatment with a dual encoder architecture combining CNN and Transformer for context data. This transformative approach could revolutionize acne diagnosis and treatment.

Y. Lin et al [9] introduced an innovative method employing Convolutional Neural Networks (CNN) for assessing the severity of acne worldwide, an important step in the development of a customized acne treatment plan. Their framework combines adaptive image preprocessing and SFNet CNN to enhance color contrast in skin and lesions, achieving 84.52% accuracy.

K. Vasudeva et al [10] offered computer vision-based approaches for automated lesion identification, lesion categorization, counting of acne and benign skin cancers, and tracking of acne severity. A CNN model trained on acne and benign skin cancer images reached a remarkable 96.4% accuracy. It employs computer vision for lesion detection, classification, and tracking, offering objective and effective skin condition diagnosis with potential therapeutic applications.

III. METHODOLOGY

1. Data Collection: The dataset [11] utilized in this study is sourced from Kaggle, a renowned website. It The dataset comprises 2357 diverse skin lesion photos, aiding in the creation and testing of classification and detection models for various skin disorders.

2.Data Preprocessing: Skin lesion images were prepared for the model with resizing to 224x224 pixels and pixel value normalization. By extending the dataset and enhancing model generalization, the dataset was divided into sets for training, validation, and testing.

3.Model Selection: Upon extensive research and analysis, we have carefully chosen the following pre-trained CNN models for skin lesion classification: AlexNet, InceptionV3, VGG16, InceptionResNetV2, MobileNet, and Xception. These selections were made due to their outstanding performance on ImageNet and their exceptional transfer learning capabilities.

4.Transfer Learning: Utilize transfer learning by removing the top layers (fully connected layers) of the selected pre-trained model. These layers are specific to the original classification task (e.g., ImageNet). Adding custom fully connected layers on top of the remaining convolutional layers to adapt the model for the skin lesion classification task.

5. Model Compilation and Training: Compiled the model with an appropriate loss function (i.e., categorical cross-entropy), optimizer (i.e., Adam), and evaluation metric (i.e., accuracy). Training the model using the preprocessed skin lesion images, split into training and validation sets. Implementing early stopping with a patience parameter to avoid overfitting and halt training when the validation loss does not improve for a twenty number of epochs.

6. Model Evaluation: During training, the models' performance is monitored on both the training and validation sets. The loss and accuracy values are recorded for each epoch to track the model's progress during training.

7. Result Analysis: During result analysis, the skin lesion classification deep learning model demonstrated significant promise, scoring an amazing 92.54% overall accuracy on the test data. It successfully classified nine different lesion types, excelling especially in differentiating between nevus and basal cell carcinoma. Dermatologists can use the confusion matrix to help with early lesion detection and diagnosis by seeing how accurate and inaccurate predictions were.

IV. IMPLEMENTATION

Algorithms:

SVM: Support Vector Machine (SVM) [12] is a potent supervised machine learning method used for regression and classification tasks. Although the term "regression" is frequently used, the actual goal is categorization. An N-dimensional hyperplane is desired by SVM for effective categorization. Data is effectively classified by SVM, a flexible tool for many classifications, by finding the best hyperplane.

DT: A decision tree (DT) [13] is a graph that employs a branching method to show each outcome that might be obtained from an input. A graphical program or specialized software can be used to automatically produce decision trees. When a group must make a decision, choice trees may help to keep the conversation on the topic.

Random Forest: One of the most significant issues with Decision Trees is diversity, and a Random Forest [14] is a machine-learning technique that addresses this issue. Despite its adaptability and simplicity, decision trees are a greedy algorithm. It focusses on optimizing for the present node split rather than how that split affects the entire tree.

MLP: Another technique for layer-based artificial neural networks is the multi-layer perceptron (MLP) [15]. While a single perceptron may solve clearly linear challenges, it is not well suited for non-linear applications. To solve these complex issues, MLP could be used.

Voting classifier: Voting classifiers [16] are machine learning estimators that train a lot of base models or estimators and provide predictions based on each base estimator's output. Voting options may be connected to aggregating standards for every estimator result.

AlexNet: AlexNet [17] is an eight-layer convolutional neural network. It utilizes a pre-trained model trained on a vast ImageNet database containing over a million photos. This model can be loaded to identify over a thousand different item categories in photos, including objects like pencils, mice, keyboards, and various animals. The network's training enables accurate recognition and classification of these categories based on the learned features from the extensive dataset.

InceptionV3: A CNN-based deep learning model called Inception V3 [18] is used to categorize photos. The model is the result of numerous theories that different researchers have studied over time. The Inceptionv3 architecture, which is frequently "pre-trained" using ImageNet, has been used in a number of applications.

VGG16: A neural network based on convolution with 16 layers is called the VGG-16 [19]. It classifies 1000 photographs with 92.7% accuracy using a variant of the VGG16 algorithm, a prominent method for photo classification by transfer learning. VGG-16 is a sizable network with roughly 138 million parameters.

Inception ResNetV2: Inception-ResNet-v2 [20] replaces the filter concatenation stage of the original Inception architecture with residual connections, hence increasing the potential of the Inception family of architectures. trained on more than one million images from the ImageNet database. The 164-layer network can categorize images of photographs into 1000 different things, such as keyboards, mouse, pens, and other animals.

MobileNet: Convolutional neural network (CNN) for mobile and embedded vision applications is called MobileNet [21]. Depthwise separable convolutions, which are fast deep neural networks for embedded and mobile systems, are used to build them.

Xception: The Xception model [22] is modeled around the Inception architecture and created to deliver cutting-edge performance on picture classification tasks. The Xception model makes use of depthwise separable convolutions, a type of factorized convolutions that separate the channel-wise convolution process from the spatial convolution process. While preserving a high level of representational capacity, this factorization drastically decreases the model's computational cost and parameter count.

V.RESULTS AND ANALYSIS

SVM: The SVM classifier is trained using the training data, and the test data is used to assess its performance. The plot presents a visual depiction of the confusion matrix, as illustrated in Figure 1, and the confusion matrix itself offers insights into the classifier's accuracy and misclassification rates.

DT: After training on the training data, the Decision Tree classifier is employed to evaluate its performance using the test data. By utilizing the confusion matrix, valuable information about the classifier's accuracy and misclassification rates can be obtained. Additionally, a visual representation of the confusion matrix in the form of a plot further enhances the understanding of the classifier's performance as shown in Figure 2.

Random Forest: The Random Forest classifier undergoes a two-step process: training on the provided training data and subsequent evaluation on the test data. To assess the classifier's accuracy and misclassification rates, the confusion matrix is employed, while a graphical representation of the confusion matrix in the form of a plot offers a visual depiction. The Random Forest classifier leverages ensemble learning methods by combining numerous decision trees, enabling it to enhance accuracy and mitigate overfitting issues as shown in Figure 3.

MLP Classifier: MLP (Multi-Layer Perceptron) classifier using the training data, and evaluating its performance using the test data. By examining the confusion matrix, one can gain insights into the classifier's precision and misclassification rates. Additionally, a plot is generated to visualize the confusion matrix. The MLP classifier is capable of recognizing patterns which are complex and relationships in data due to its multiple layers of interconnected nodes (neurons). Backpropagation and gradient descent techniques are used to optimize the network's weights and biases, as demonstrated in Figure 4.

Voting Classifier: The Voting Classifier combines the predictions of multiple classifiers (SVC, Random Forest Classifier, Decision Tree Classifier) by majority voting to make the final prediction. The individual classifiers may have different strengths and weaknesses, and the Voting Classifier leverages their collective decision-making to improve overall performance. The confusion matrix provides insights into the classifier's accuracy and misclassification rates, while the plot offers a visual representation of the confusion matrix as shown in Figure 5.

AlexNet: The AlexNet model's groundbreaking architecture, developed with TensorFlow's Keras API, changed deep learning. The approach includes activation functions, batch normalization, convolutional layers (CL), pooling layers, fully connected layers, and dropout regularization. The input shape of the model is (224, 224, 3), which denotes the height, width, and RGB channels of the input image. The model is composed of several CL, each followed by batch normalization and ReLU activation. The first and fifth convolutional layers are followed by two max-pooling layers. Before sending the output to fully linked layers, it is flattened, dropout regularization, and ReLU activation are applied. The final output layer creates probabilities for 9 classes using batch normalization and softmax activation, as shown in Figure 6.

InceptionV3: Pre-trained weights are included in the InceptionV3 model for classification, although connected layers are not. Additional layers are added to the model to improve it, including a fully connected layer for multi-class classification utilizing softmax activation and global average pooling for lowering dimensions. The final model's summary is shown. By assembling the model with an optimizer, loss function, and metric, the model is made ready for training. The fit_generator() function is used for training, and the training and validation data, epochs, and batch size are all supplied. If the loss doesn't get better, early quitting is used. The model is saved in H5 format after training. As seen in Figure 7, a training history visualization is made to evaluate loss and accuracy and help spot overfitting or underfitting problems.

VGG16: For a classification assignment with 9 classes, the VGG16 model was trained. With the exception of the top layers, pre-trained weights from ImageNet are used to initialize the VGG16 architecture. For prediction, a fully connected layer with softmax activation is included. Categorical cross-entropy loss and the Adam optimizer are used in the model's construction. 20 training epochs are completed, with early termination based on loss. Through the use of Matplotlib, the training history is shown, displaying the development of loss and accuracy over both training and validation. As seen in Figure 8, this visualization aids in evaluating the model's performance and spotting over- or underfitting.

Inception ResNetV2: An eight-class classification challenge is used to train the Inception ResNetV2 model. Importing the model and setting up its architecture, which uses pre-trained weights from ImageNet, are the first steps. The Adam optimizer and categorical cross-entropy loss are used to assemble the model after that. As demonstrated in Figure 9, training is carried out across 20 epochs with an Early Stopping callback to track loss and avoid overfitting.

MobileNet: The given code employs the MobileNet model to tackle a classification task involving 9 different classes.
The MobileNet model uses pre-trained ImageNet weights, excluding the final layers. It adds a flattened layer and a 9-unit softmax prediction layer. Compilation involves categorical cross-entropy loss and Adam optimizer. Early Stopping is employed to track training loss, as depicted in Figure 10.

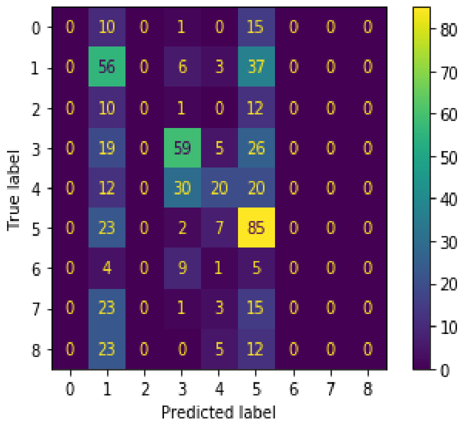

Figure 1: Matrix of confusion for SVM classifier

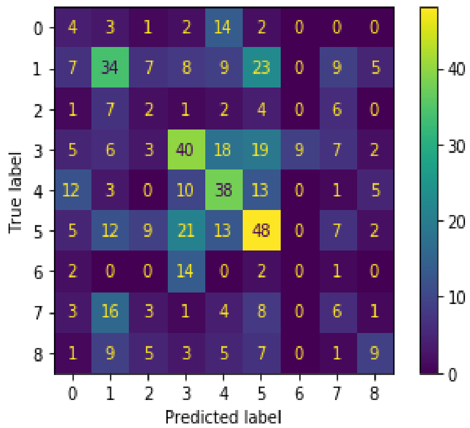

Figure 2: Confusion matrix for DT classifier

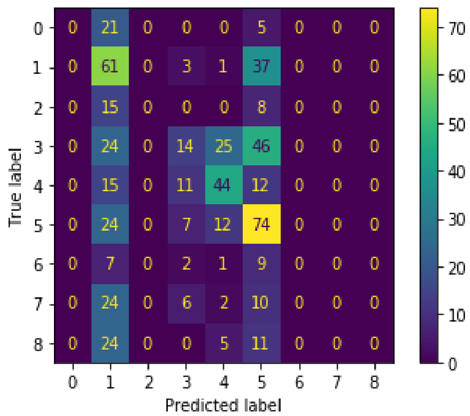

Figure 3: Confusion matrix for Random Forest

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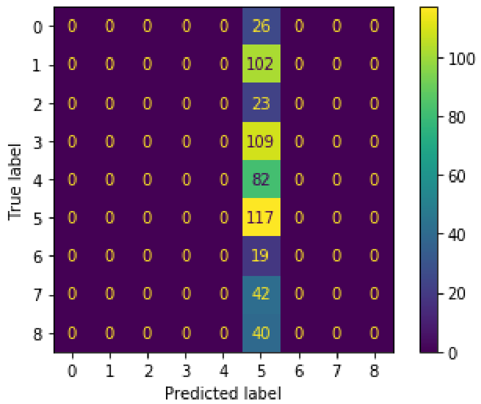

Figure 4: Confusion matrix for MLP Classifier

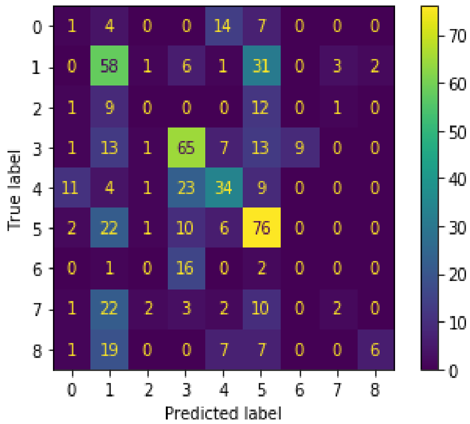

Figure 5: Confusion matrix for Voting Classifier

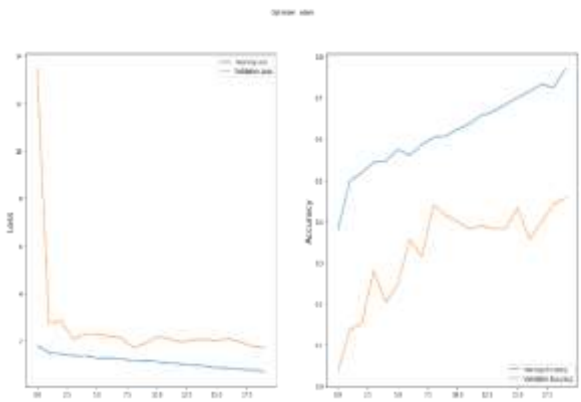
Figure 6: Training and Validation loss and accuracy graphs of AlexNet.

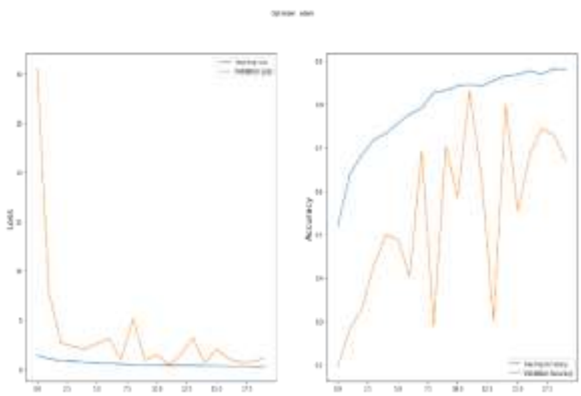
Figure 7: Training and validation of loss and accuracy graphs of inception v3 model.

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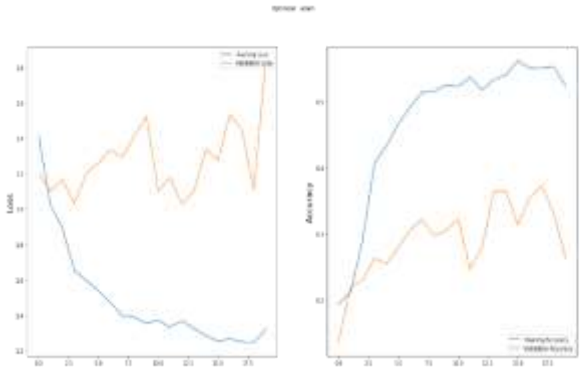

Figure 8: Training and Validation loss and accuracy graphs of VGG16.

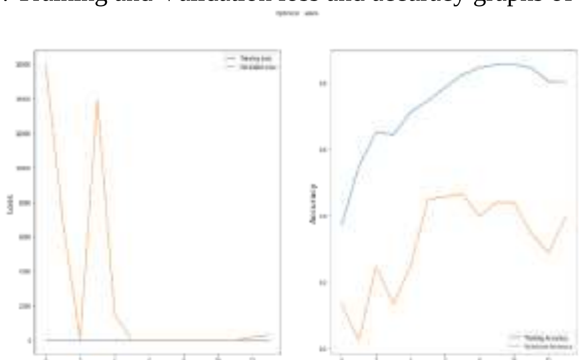

Figure 9: Training and Validation loss and accuracy graphs of Inception ResNetV2.

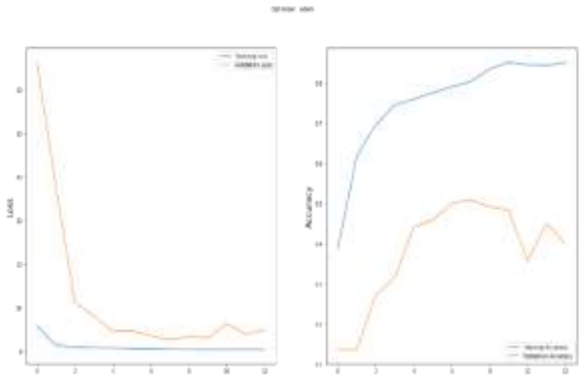

Figure 10: Training and validation of loss and accuracy graphs of MobileNet model.

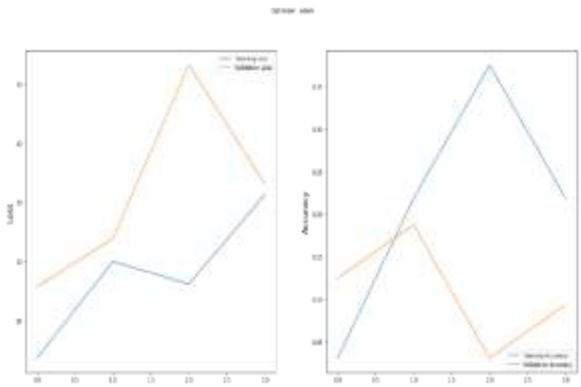

Figure 11: Training and validation of loss and accuracy graphs of Xception model.

Xception: The given code performs classification on 9 different classes using the Xception model. The final layers are not loaded; only pre-trained ImageNet weights are. It also includes a flattened layer, a 9-unit softmax prediction layer, categorical cross-entropy loss, and the Adam optimizer during compilation. Using both training and validation data, training lasts for 20 epochs. The model is saved as 'xception.h5' and the training progress is monitored in 'r1'. As seen in Figure 11, Matplotlib depicts the training history with loss and accuracy in 'x'.

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VI. CONCLUSION AND FUTURE SCOPE

This paper presents a fully automated end-to-end CNN-based network designed for categorizing skin lesions. A large collection of 2357 skin lesion photos from reliable websites is used in the study to provide a diverse and representative sample. The dataset went through a thorough preprocessing procedure that included dataset splitting, image resizing, normalization as well as data validation, cleaning, augmentation, and normalization. These processes made sure that the dataset was reliable, consistent, and appropriate for deep CNN model training.

In this paper, a completely automated, end-to-end CNN-based network for classifying skin lesions is presented. For the study, a vast collection of 2357 images of skin lesions from reputable websites was gathered to create a diverse and representative sample. The dataset underwent a thorough preprocessing process that includes separating the dataset, resizing the images, normalizing the data, and validating, cleaning, enhancing, and normalizing the data. Through these procedures, the dataset was verified to be trustworthy, consistent, and suitable for deep CNN model training.

Future developments in model architectures, multimodal analysis, interpretability, deployment in online and mobile applications, collaborative dataset creation, integration with clinical workflow, and ongoing evaluation and validation will determine the scope of skin lesion classification and detection using deep CNN models. These developments have the potential to transform dermatological practice, increase the reliability of diagnostics, and improve patient care.

REFERENCES

[1] F. Santos, F. Silva and P. Georgieva, "Transfer Learning for Skin Lesion Classification using Convolutional Neural Networks," 2021 International Conference on Innovations in Intelligent Systems and Applications (INISTA), Kocaeli, Turkey, 2021, pp. 1-6, doi: 10.1109/INISTA52262.2021.9548455.
[2] J. Aguilar et al., "Towards the Development of an Acne-Scar Risk Assessment Tool Using Deep Learning," 2022 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC), Ixtapa, Mexico, 2022, pp. 1-6, doi: 10.1109/ROPEC55836.2022.10018763.
[3] K. Rezaee, M. R. Khosravi, L. Qi and M. Abbasi, "SkinNet: A Hybrid Convolutional Learning Approach and Transformer Module Through Bi-directional Feature Fusion," 2022 International Conference on Computing, Communication, Security and Intelligent Systems (IC3SIS), Kochi, India, 2022, pp. 1-6, doi: 10.1109/IC3SIS54991.2022.9885591.
[4] F. Santos, F. Silva and P. Georgieva, "Out of Training Distribution Detection for Multi-Class Skin Lesion Diagnosis," 2021 International Conference on Innovations in Intelligent Systems and Applications (INISTA), Kocaeli, Turkey, 2021, pp. 1-6, doi: 10.1109/INISTA52262.2021.9548595.
[5] Mohakud, Rasmiranjan & Dash, Rajashree. (2021) "Designing a grey wolf optimization based hyper-parameter optimized convolutional neural network classifier for skin cancer detection". Journal of King Saud University - Computer and Information Sciences. 34. 10.1016/j.jksuci.2021.05.012.
[6] Fantini, Irene & Yasuda, Clarissa & Bento, Mariana & Rittner, Leticia & Cendes, Fernando & Lotufo, Roberto. (2021). "Automatic MR image quality evaluation using a Deep CNN: A reference-free method to rate motion artifacts in neuroimaging". Computerized Medical Imaging and Graphics. 90. 101897. 10.1016/j.compmedimag.2021.101897.
[7] A.Kumar, A. Vishwakarma and V. Bajaj, "Automatic Classification of Multi-Class Skin Lesions Dermoscopy Images Using an Efficient Convolutional Neural Network," 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 2023, pp. 1-5, doi: 10.1109/SCEECS57921.2023.10062981.
[8] M. S. Junayed, M. B. Islam and N. Anjum, "A Transformer-Based Versatile Network for Acne Vulgaris Segmentation," 2022 Innovations in Intelligent Systems and Applications Conference (ASYU), Antalya, Turkey, 2022, pp. 1-6, doi: 10.1109/ASYU56188.2022.9925323.
[9] Y. Lin, Y. Guan, Z. Ma, H. You, X. Cheng and J. Jiang, "An Acne Grading Framework on Face Images via Skin Attention and SFNet," 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Houston, TX, USA, 2021, pp. 2407-2414, doi: 10.1109/BIBM52615.2021.9669431.
[10] K. Vasudeva and S. Chandran, "Classifying Skin Cancer and Acne using CNN," 2023 15th International Conference on Knowledge and Smart Technology (KST), Phuket, Thailand, 2023, pp. 1-6, doi: 10.1109/KST57286.2023.10086873.
[11] https://www.kaggle.com/datasets/nodoubttome/skin-cancer9-classesisic
[12] https://www.javatpoint.com/machine-learning-support-vector-machine-algorithm
[13] https://www.geeksforgeeks.org/decision-tree-introduction-example/
[14] https://www.javatpoint.com/machine-learning-random-forest-algorithm
[15] https://www.javatpoint.com/multi-layer-perceptron-in-tensorflow

[16] https://www.geeksforgeeks.org/ml-voting-classifier-using-sklearn/
[17] https://www.geeksforgeeks.org/ml-getting-started-with-alexnet/
[18] https://iq.opengenus.org/inception-v3-model-architecture/
[19] https://www.geeksforgeeks.org/vgg-16-cnn-model/
[20] https://medium.com/@zahraelhamraoui1997/inceptionresnetv2-simple-introduction-9a2000edcdb6
[21] https://www.geeksforgeeks.org/image-recognition-with-mobilenet/
[22] https://arxiv.org/pdf/1610.02357.pdf
[23] R. Ponnala and C. R. K. Reddy, "Hybrid Model to Address Class Imbalance Problems in Software Defect Prediction using Advanced Computing Technique," *2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, Salem, India, 2023, pp. 1115-1122, doi: 10.1109/ICAAIC56838.2023.1014137