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A COMPARATIVE STUDY OF CONVOLUTIONAL NEURAL NETWORKS (CNN) AND INCEPTION V3 FOR FACIAL SKIN DISEASE CLASSIFICATION

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Article Info

Abstract

Acne and the malignant skin condition basal cell carcinoma along with other skin diseases dramatically affect global health. The promising capabilities of deep learning in dermatological classification exist only for isolated disease groups since studies exclusively analyze individual conditions without covering entire facial skin disorders. The study investigates CNN and Inception V3 models for the classification of five important conditions which include acne and actinic keratosis with basal cell carcinoma and eczema followed by rosacea. A total of 1,250 validated DermNet images were used for processing which included resizing along with normalization techniques and data enhancement methods. The Inception V3 model operates with implemented dense layers but a custom CNN model runs with an original structure of 5 convolutional and 2 dense layers. Both used Adam optimization and categorical cross-entropy loss. The test accuracy levels from Inception V3 (94%) outperformed those of CNN (93%) and the precision and recall coefficient reached 0.83 macro averages. The optimization process in CNN revealed overfitting since the training accuracy reached 88% while the test accuracy only reached 80%. Inception V3 outperformed other models by achieving F1 scores of 0.84 for rosacea and 0.86 for acne but CNN proved slightly better at identifying eczema with an F1 score of 0.81. The investigation proved that Inception V3 exhibits strong capabilities for diagnosing facial skin diseases through accurate scalable results. Despite dealing with restricted data the model kept outstanding performance levels through its implementation of transfer learning skills. Future research must increase the dataset size while conducting clinical tests to enhance universal usage. This research enables automated dermatological diagnosis to specifically identify five conditions which do not have current complete deep learning-based solutions.

Keywords: *Deep learning, skin disease classification, Inception V3, CNN, transfer learning, dermatology.*

1. Introduction

Skin diseases can be caused by internal causes such as hormones (e.g., acne) or by external causes such as pollution and sun. Scabies and lice are viral infections, whereas psoriasis and atopic eczema are long-term illnesses. Skin diseases are mostly neglected by most people and they never visit clinics. Skin diseases constitute 1.79% of health diseases worldwide [1].

Face skin problems are popular and can remarkably lower an individual's standard of living [2]. These can range from more serious illnesses like acne and eczema cell carcinoma to more major ones like benign ailments like melanoma and basal [3]. The World Health Organization estimates that skin cancer makes up about one-third of all cancer types. As more people develop skin cancer each year, more people die from it. There are now 132,000 melanoma cases and 3 million non-melanoma instances of skin cancer reported each year worldwide [4]. The process of detecting and classifying skin illnesses according to their clinical and pathological characteristics is known as skin disease categorization [5, 6]. Every day, 9500 people in the US simply receive a skin cancer diagnosis, and 2 individuals die their lives due to the illness every hour [7]. Every day, 9500 people in the US simply receive a skin cancer diagnosis, and 2 individuals die their lives due to the illness every hour [7]. Treatment for such situations typically costs USD 3.3 or USD 4.8 per year. Annual reports of newly diagnosed melanoma cases in Europe exceed 100,000. On the other side, there are 15,229 melanoma cases recorded per year in Australia. The most recent data, however, indicates that since 1990, the rate of skin cancer cases has increased [8]. According to data, aggressive melanoma cases have risen by 47% during the past ten years [9].

Acne develops when oil combined with deceased skin cells block hair follicles to create facial and body areas such as the face and neck with pimples and blackheads or whiteheads and cysts as illustrated in Figure 1. The condition has negative effects on personal esteem along with life quality. Patients receive treatment through medications that apply to the skin and those that take orally along with recommended lifestyle changes [10]. The pilosebaceous unit inflammation that causes acne vulgaris develops as a persistent skin condition which affects body performance and mental peace. The condition impacts about 85% of teenage individuals and more than 10% of adults throughout their lifetime. According to worldwide disease burden calculations acne stands as the eighth most prevalent condition occupying 9% of all diseases [11-13].

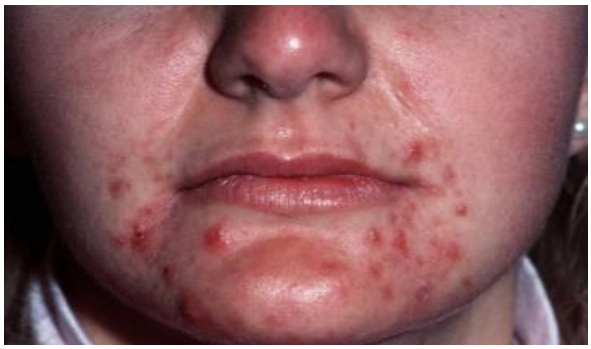

Figure 1. Sample of Acne

As illustrated in Figure 2 actinic keratosis appears as scaly skin growths that manifest on sun-uncovered zones and affects primarily individuals with light complexion. The disease develops into squamous cell carcinoma when someone spends extended amounts of time under the sun. Cryotherapy combined with topical medicines and PDT serve as accepted treatment solutions for this condition [14]. The proliferation of keratosis tissue from Actinic Keratosis (AK) creates vulgar skin surfaces with varied pigmentation and scaly dyplomata. UV exposure together with genetics and the condition of the immune

system often leads to this skin problem which mostly affects Caucasian elderly adults during middle age. The skin condition AK frequently appears as either reddish-brown or yellowish spots and becomes a risk factor for developing squamous cell carcinoma (SCC) at a rate of 10%. Cryotherapy or laser therapy should be used early in the treatment process because they help stop cancer development and increase life quality [15, 16].

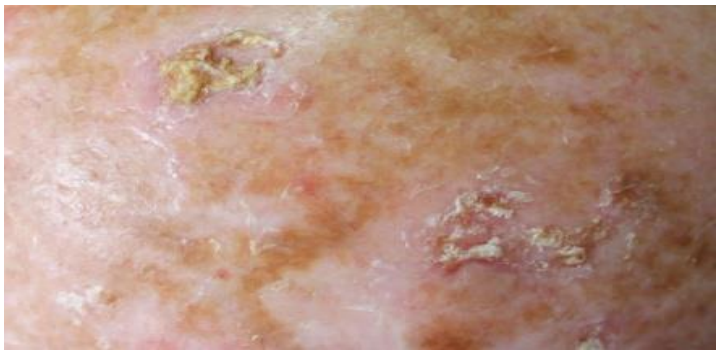

Figure 2. Sample of Actinic Keratosis

Basal Cell Carcinoma (BCC) represents the most popular form of skin cancer which creates small glossy swellings or persistent sores that result from UV radiation just like the illustration in Figure 3. This skin condition occurs most often in people with lighter complexions yet grows slowly so patients need immediate medical care to stop potential facial disfigurement [17]. Basal cell carcinoma (BCC) stands as the most prevalent form of skin cancer in the United States, with a staggering 2 million annual diagnoses. The moderate rate of inaccurate diagnosis raises the necessity for invasive tests through biopsy because BCCs typically develop in important face regions. A large number of patients deal with multiple BCCs thus making diagnostic challenges more crucial [18]. Doctors traditionally need visual examination through dermoscopy for diagnosing BCC. The detection of BCC by dermoscopy shows very strong sensitivity but presents problems in specificity which reaches a lowest level at 53.8%[19].

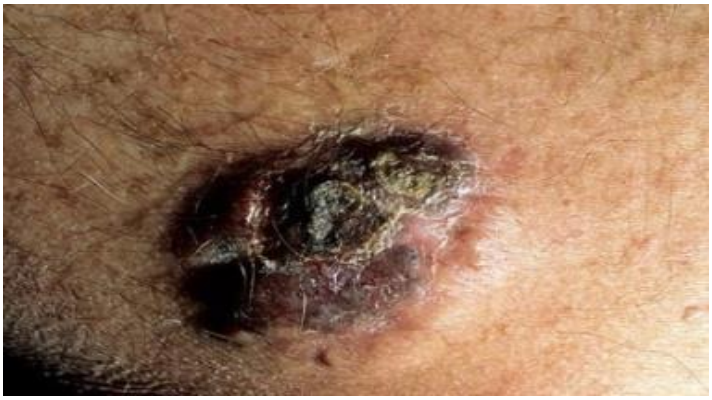

Figure 3. Sample of Basal Cell Carcinoma

Eczema exists as atopic dermatitis which represents a persistent skin condition while producing skin regions that become both inflamed and red together with intense itching as illustrated in Figure 4. Eczema affects different regions of the human body yet the skin of hands, feet and face remains the most frequent location for its appearance. The development of eczema occurs through genetic and environmental factors because this condition emerges from different sources such as allergies and pollution along with anxiety and weather changes [20]. Different types of medical care including topical solutions and oral medications together with lifestyle measures treat eczema by helping people identify

and avoid their triggers while moisturizing themselves frequently [21]. Multiple triggers exist to start eczema symptoms such as inherited genes together with environmental elements and stress and allergic reactions. Patients with eczema experience no permanent recovery but can control its symptoms through different treatment options including topical creams with oral medications and lifestyle modifications [22].

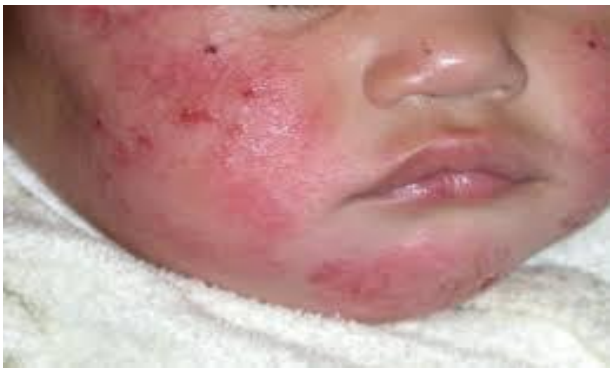

Figure 4. Sample of Eczema

The skin disease known as psoriasis causes millions worldwide to develop inflamed red scaly areas which may be accompanied by pain [23]. Medical professionals define psoriasis as an autoimmune condition because faulty immune responses attack normal skin cells [24].

Rosacea affects adults aged 30 and above who have fair skin through its visible signs of blood vessels along with red skin patches and flushing condition as shown in Figure 5. The condition gets mistaken for other skin diseases because it shares similar signs of inflammation with them [25].

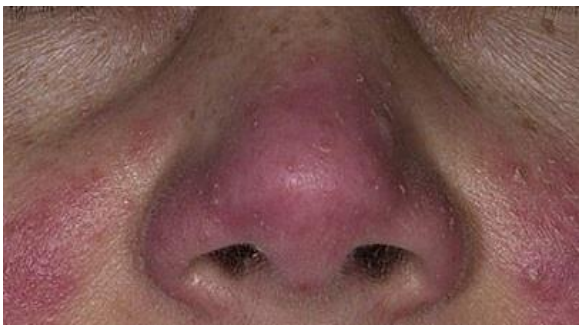

Figure 5. Sample of Rosacea

Four types of triggers activate these conditions: heat exposure, sun exposure, stress and particular foods. The disease progression may cause both skin thickening alongside papules and pustules to appear. The treatment plan combines topical medicines and oral medications together with laser interventions and houses keeping adjustments [26, 27].

The five forms of facial skin diseases include Acne alongside Actinic Keratosis and Basal Cell Carcinoma with both Eczema and Rosacea. Different skin conditions including the everyday acne along with the severe health issue of skin cancer (Basal Cell Carcinoma) present diagnostic and therapeutic difficulties to healthcare providers. Visual examination by dermatologists serves as the traditional diagnosis method yet shows inconsistency among observers. Machine learning with deep learning techniques have recently received attention because of their successful disease classification ability [28].

The ability of automated classification systems to handle dermatology shortages and enhance diagnosis depends on the use of reliable testing methods with clean data sources [29].

Machine and deep learning tools have become widely used for diverse medical applications such as problem detection and solution classification in recent periods [4, 28]. The medical sector uses Deep learning as an advanced technique under machine learning classification methodologies to perform diverse diagnostic tasks. Scientists have shown their ability to analyze kidney diseases alongside Alzheimer's illness and cancer of the breast and alopecia areata and malignancies of the brain [30, 31].

Deep-learning algorithms have shown success in identifying and classifying various skin dermatology-affected problems during multiple research studies [28]. The Mask RCNN technology enables developers to create systems for analyzing skin samples [32]. The CNN architecture enables transfer learning applications which detect skin problems along with performing skin image classification [6], among malignant-melanoma, basal-cell carcinoma, actinic-keratosis, squamous cell carcinoma, and psoriasis [10]. Multiple techniques share the common objective of sorting different kinds of skin ailments. The best of our knowledge indicates no deep learning techniques classify the five various skin disorders which include Acne and Actinic Keratosis and Basal Cell Carcinoma and Eczema and Rosacea..

Acne alongside rosacea and eczema and actinic keratosis and basal cell carcinoma affect millions worldwide making diagnosis exceptionally difficult. The current diagnostic methods require human expert evaluation together with manual inspections which prove to be both slow and prone to mistakes. Classifying skin diseases presents significant limitations for the prediction accuracy attained by previous machine learning models. Rising disease numbers coupled with insufficient dermatologists demand fast deployment of automated medical devices because of the present-day challenge.

This research aims to enhance the recognition of five common skin diseases through deep learning methods. The identification of conditions particularly skin cancer needs immediate attention but existing detection procedures tend to be slow and subjective which delays the necessary treatment period. Organization methods that tackle patient volume growth and reduced healthcare resources need efficient automatic classification systems.

Most existing research about machine learning for skin disease classification has not focused on specific identification of these five conditions. The research fills this knowledge gap through development of deep learning technology intended for facial skin disease diagnosis. This proposed solution brings together three main benefits which includes improved diagnostic accuracy coupled with faster assessment processes while assisting dermatologists especially in areas where medical support is scarce.

2. Literature Review

Techniques of deep learning offer substantial benefits to skin research fields. The techniques demonstrate success in identifying and sorting skin issues with a focus on dangerous diseases such as psoriasis and melanoma. Automatic skin problem classification helps doctors make early diagnoses through its application. The diagnosis of skin sickness requires several procedures which use flame control methods across various categories. The system development utilizes a fully programmed strategy together with implementation of a CNN model. The research benefits from HAM1000 database selection which includes seven possible carcinogenic conditions and actinic keratosis and five other skin problems and achieves 90% accuracy through the CNN model analysis [8]. A home-based system functions to perform the classification of skin problems directly from home settings. The device operates

through skin image inputs to differentiate between melanocytic and normal skin lesions because it implements CNN functionality. The classification methods achieve 82% accuracy for detecting skin diseases with ease [33].

The VGG Signet model serves as a tool for dermatology cancer classification when given dermoscopy images as input. The researchers presented the CNN which delivered an accuracy rate of 97 percent. The findings presented here demonstrate how modern facilities along with CNN-driven techniques create improved solutions for skin melanoma evaluation which provides essential medical information to practitioners [34]. A research group developed an accurate method for skin lesion recognition particularly for malignant melanoma through the use of facial region-based Convolutional Neural Network (RCNN) and transfer learning-based methodology. The testing method with strong criteria showed accuracy at 96% and again at 94% and once more at 88% using three separate datasets named ISBI2016-2017 and HAM1000. The research demonstrates how transfer learning combined with RCNN-based methods could enhance skin lesion detection automation for medical applications in cancer screening [35].

Investigators worked on uniting machine learning systems with deep learning (DL) approaches for skin abnormality identification tasks. Numerous studies have established that support vector machine along with k-nearest neighbor, k-means clustering and Naive Bayes yield inferior results when compared to deep learning specifically CNN [citations]. DL provides automatic feature extraction which improves diagnosis results while bringing innovative improvements to dermatology [36]. Medical experts use image enhancement methods to discover and identify melanoma skin abnormalities. Academic researchers employed the PH2 dataset to create a tool for examining skin tissue which enables doctors to distinguish melanoma from common nevi. The research analyzed class imbalance using SMOTE alongside deep CNNs especially Squeeze Net and demonstrated deep learning effectiveness in detecting melanoma [37]. A research investigation of psoriasis employed model selection and tuning techniques on K-NN, Random Forest and DNNs, SVM and Naive Bayes to observe their effect on prediction accuracy levels [38].

Research reference [39] demonstrates that CNN delivered superior results than all analyzed methods. The CNN model achieved superior results than other techniques on ninety skin lesion photos of psoriatic patients as it produced accuracy rates starting from seventeen percent down to minimal levels. The research findings demonstrate how deep learning models primarily through CNNs enhance the accuracy and reliability when identifying psoriasis from skin pictures [40]. Skin disease classification through both machine learning and deep learning techniques has experienced significant advancements during the recent years. Since 2018 CNNs have been used to distinguish between psoriasis and melanoma skin conditions and subsequent studies showed similar effectiveness. The classification of various skin conditions occurred through RF and KNN and RCNN and CNNs after 2021. According to research from 2022–2023 the medical diagnostic models like EfficientNetV2, Inception-ResNet-v2 and ResNet-18 proved their ability to accurately identify multiple diseases through deep learning advancement [28]. Computer vision problems benefit from enhanced efficiency through CNN as opposed to conventional methods. The models extract deep features consisting of skin color and texture values. The model achieves improved accuracy in face skin disease detection when using this method [41]. An Android application with phone camera accessibility features for photography has been developed using TensorFlow Lite running on the phone to identify dermatological conditions. The system maintained 74% accuracy when it identified seven different skin diseases through its assessment [42]. A Various writer structured a classification model to identify skin conditions in specific disease groups. During the modeling evaluation phase the methodology achieved 84 percent accuracy among all classifications [43].

The proposed research design of Inception Net architecture optimization adds augmented data features alongside new layers to detect both melanoma and non-melanoma skin cancers. Research claims that the optimized model utilizes two optimizers named Adam and Nadam to enhance performance on 2637 Kaggle images thus providing dependable dermatological diagnosis support at the early stages of patient care [44]. A research examines deep learning applications to detect Dermatological conditions which focus on identifying facial skin diseases. The research analyzes eleven CNN models that process more than 25,000 medical images containing eight different skin disease categories. ResNet152 achieved the highest performance levels in accuracy as well as recall and precision results among all systems while analyzing a test sample of 1930 images according to research findings [45].

2.1. Deep Artificial Neural Networks (ANNs)

The subfield of AI known as machine learning develops algorithms that acquire knowledge and improvement abilities through unprogrammed processing of data. The system attempts to build capabilities in acquiring knowledge from training data. The different machine learning categories consist of supervised and unsupervised together with reinforcement learning. According to this study supervised learning remains the main focus because each training sample holds an expected outcome label while suggesting additional readings about alternative learning models [46-48].

The main objective of supervised learning aims to correctly label both training and test samples. A normal learning type in classification tasks decides the placement of input samples into categories by looking for particular data attributes during training sessions. Among the broad usage of Artificial Neural Networks (ANNs) in supervised learning there exist specific ANN models which can be trained with unsupervised methods [49]. Neural networks take their inspiration from biological neural systems to create their distributed structure which organizes interdependent neurons. Deep learning uses multiple layer ANNs to improve pattern recognition capabilities of the system as illustrated in Figure 6. Various machine learning operations benefit from these models which perform exceptionally well in classification tasks. The processed features identified in initial layers transform into advanced representations as depth increases in layers [50].

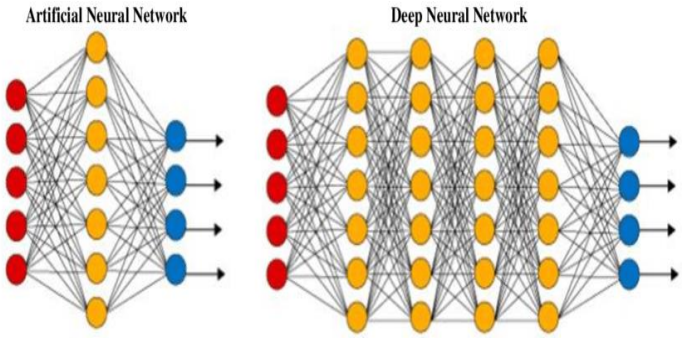

Figure 6. Basic structure of Deep Artificial Neural Network [51]

2.2. Convolutional Neural Network (CNN)

Because of surface performance and few preprocessing demands CNNs established years ago are now being widely used for object detection alongside speech recognition [47]. According to Oppenheim and Schafer dynamics of linear superposition (Equations 1 and 2) [52], define convolution between functions f and g.

$$H(x) = (f * g)(x) = \int f(u)\, g(x - u) \qquad (1)$$

Since photographs maintain a discrete two-dimensional shape instead of integral structure the integral expression can be replaced with summation then followed by two-dimensional convolution.

$$h(x) = (f * g)(x) = \sum_u \sum_v f(u,v)\, g(x - u, y - v) \qquad (2)$$

The CNN filters (f) process input image (g) to generate output image (h) through each layer of operations as demonstrated in Figure 7. A system of generating feature maps applies multiple filters simultaneously to train diverse weights for each map. During training the training process allows adjustments of stride values along with filter count and kernel dimensions. The entire image receives its weight data from a single set which facilitates weight sharing thus decreasing the number of free parameters and boosting both model effectiveness and generalization potential [48].

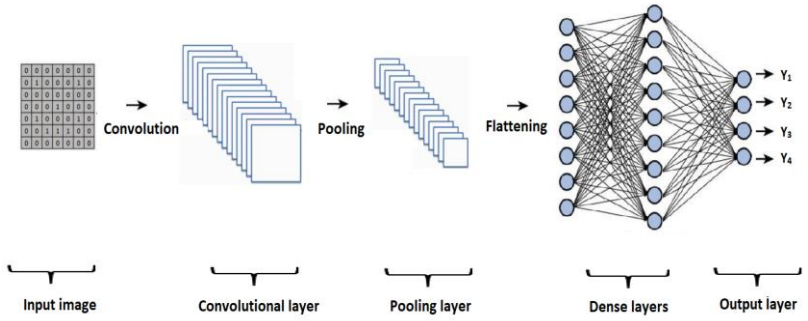

Figure 7. A Basic Structure of CNN [53].

2.3. Research Gap and Objectives

Several research papers indicate a major deficiency exists in the field of dermatological study that addresses automated diagnosis methods for five particular skin conditions including Acne, Actinic Keratosis, Basal Cell Carcinoma, Eczema, and Rosacea. There exist limited research which applies machine learning (ML) and deep learning (DL) techniques to classify the mentioned skin diseases. The diagnostic capability of DL models remains unexplored extensively for Acne and Eczema conditions along with three other dermatological diseases in previous research.

The literature contains few examples of deep learning used for skin image classification. Research has established that automatically derived high-level features by DL techniques demonstrate significant potential for system improvement. This research develops a new framework built with DL techniques to analyze five skin diseases while offering support for dermatologists through better diagnosis and quicker identification and less medical staff requirements.

The identification of melanoma using deep learning convolutional neural networks reaches 82.4% accuracy in performance rates. The VGG-SegNet along with transfer learning and the RCNN performed better than other models on benchmark assessment datasets. Results demonstrated that deep learning delivery superior performance than traditional systems including KNN and SVM as well as Naive Bayes. The classification performance improved because of image enhancement techniques which utilized SMOTE to address unbalanced datasets.

3. Methodology

3.1. Dataset Acquisition and Preparation

3.1.1. Dataset Source and Description

This research faces a substantial obstacle because there exists no exclusive dataset demonstrating images from five skin disease types comprising Acne, Actinic Keratosis, Basal Cell Carcinoma, Eczema, and Rosacea. The researchers solved this drawback through the Facial Skin Diseases dataset that they obtained by extracting each of these five categories from the primary DermNet database.

Research into facial skin disease classification systems depends on the Face Skin Diseases dataset which groups its 1250 images according to five disease groups as discussed in Table 1. The research relies on DermNet as its image source since DermNet organizes more than 23,000 clinically described skin disorders with free public access through its DermNet Skin Disorder Atlas program.

The DermNet original data collection contains skin disorder diagnoses within 23 main categories that distribute their subgroups across 642 sections alongside several redundant classifications alongside empty labels and unrelated image clusters. The research depends on data filtering to obtain necessary information.

The chosen dataset enables analysis of skin disease classification because it contains statistical data shown in Table1 regarding disease representation.

Table 1. Overview of the Dataset and Distribution of Classes

No.	Class Name	No. of Images
1	Acne	250
2	Actinic Keratosis	250
3	Basal Cell Carcinoma	250
4	Eczema	250
5	Rosacea	250

3.1.2. Dataset Splitting

For the split of data between training and validation sets and testing sets the proportions established were Training Set contained 80% of the data (904 images), Validation Set received 10% of the data (125 images) while Testing Set contained the remaining 10% of the data (125 images). Through this equal distribution the model received proper training and distinct sections preserved unbiased evaluation and modifications.

3.1.3. Image Format and Filtering

The JPEG format contains one image from each category among the five skin diseases. The dataset quality is preserved by eliminating images that are raw or possess low quality.

The deep learning model applies the classification process for determining the correct category for each image to receive. The model requires preprocessed images and cleaned data by implementing a preparatory step for its successful input. The preprocessing efforts lead to better model recognition of visual patterns within the five disease classifications..

3.2. Data Preprocessing

Deep learning workflows require the essential preprocessing stage to prepare data which results in performance and efficiency improvements of the model. The next section explains all procedures which standardized and optimized the input image dataset ahead of model training. The workflow includes three preprocessing techniques: first it resizes the images followed by normalization which scales the images and then implements data augmentation to both boost dataset quantity and model generalization.

3.2.1. Image Resizing and Scaling

A. Image Resizing

The deep learning model requires images in a consistent input dimension so the system resizes every photo to 224 × 224 pixels. This particular input dimension of 224 × 224 pixels serves as a standard default for CNNs which improves model training efficiency and allows for layer compatibility. A standardized image size enhances data processing efficiency because the neural network handles simpler inputs that remain structurally aligned.

B. Image Scaling (Normalization)

After resizing images through the process all RGB scale pixels ranging from zero to two hundred fifty-five have their values transformed to fall within the 0-1 range. The Keras ImageDataGenerator utility performs normalization of our data through its built-in process. pixel value normalization enables the model to acquire knowledge much quicker and with better results. The scaling process contributes to stable computations in training while making the model reach convergence at higher speed.

Neural networks require normalization to achieve optimal data quality because it removes gradient descent optimization constraints from pixel value magnitude variations. The resizing procedure and normalization operation establish crucial processing steps which enable the development of dependable and stable model training.

3.2.2. Data Augmentation

A. Purpose and Importance

Creating deep learning models requires sufficient labeled samples due to the scarcity of available data. Data augmentation serves as the solution for this problem. The technique creates new data variations by applying different image modifications including cropping along with rotation and flipping and zooming and shearing procedures. The applied transformations produce acceptable modifications that accurately replicate realistic changes between images while preserving their meaning.

The main objective of data augmentation practice is to grow the number of examples in the training dataset as well as enhance its diversity while increasing its variability which boosts model generalization and minimizes overfitting. A favorable effect occurs when training models small uneven datasets..

B. Common Techniques in Literature

Both CNN-based architectures such as AlexNet and studies using ImageNet-based approaches have incorporated data augmentation according to several research teams. All these research accomplishments demonstrate that augmentation enhances sample quantity while simultaneously enhancing model execution and algorithm output effectiveness. The outcome of data augmentation produces highly accurate and reliable classification results because of its functionality with diverse and unknown input datasets.

3.2.3. Augmentation Implementation in Current Study

The Keras ImageDataGenerator class enables dynamic image transformation during training as this study applies data augmentation to the model. The following parameters and transformations are used: Validation Split: 10% of the dataset is reserved for validation, and the remaining 90% is used for training, Rescaling: Images are normalized by dividing pixel values by 255, Shear Range: Applied shearing transformation to slant the image content, adding variability, Zoom Range: Introduced zoom in/out transformations to modify the image scale, Horizontal Flip: Enabled horizontal flipping to introduce mirrored versions of images, useful in tasks where left-right orientation does not impact classification.
The ImageDataGenerator object enables automatic application of augmentations which produce batches containing 32 transformed images during training. Through dynamic generation checking the model learns comprehensive patterns instead of memorized examples because the process boosts data variability.

3.3. Model Architecture and Design

3.3.1. Convolutional Neural Networks and Transfer Learning

CNNs establish themselves as the superior technology for extracting features while classifying images [54]. Noisy medical images and dermoscopic images with their related visual distortion patterns create difficulties when classifying skin biopsy images [55]. The achievement of high accuracy in these challenges depends on accessing substantial labeled datasets [56, 57] .

Transfer learning becomes an essential solution to address the dataset constraints. Transfer learning allows the use of pre-trained models produced from large datasets for new more manageable and computational less-intensive tasks. The medical image classification sector employs pre-trained models which include VGG16, VGG19, ResNet50, Mobilenet, and Inception V3. The performance and training time benefits of transfer learning stem from using visual patterns acquired through learning millions of images as demonstrated in Figure 8.

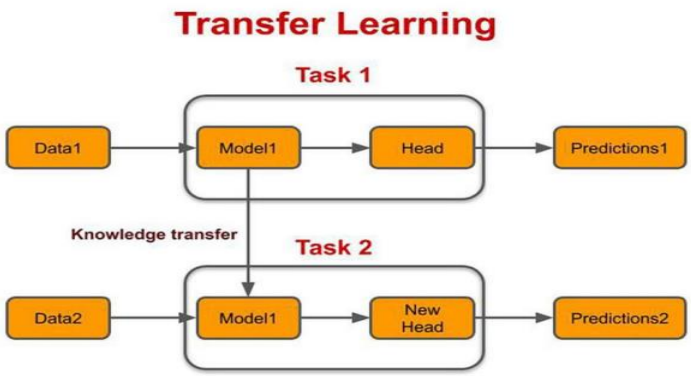

Figure 8. A basic architecture of Transfer Learning [58].

3.3.2. Inception V3 Model Overview

The research uses Inception V3 with transfer learning because it shows a high performance in complex image classification workloads particularly in medical applications with scarce data. Inception V3 uses a deep structural framework with 311 layers to operate on large-scale ImageNet dataset comprising more than a million items from its 1000 categories. The model handles input images with dimensions of 299×299 pixels for producing dense high-level visual feature patterns.

The system utilizes two fundamental sections: A CNN-based feature extraction part and a classification module with fully connected layers and a SoftMax layer.

A classification module contains fully connected layers together with a SoftMax layer. The implementation of Inception V3 reaches 78.1% top-1 accuracy together with 93.9% top-5 accuracy on the ImageNet benchmark. The paper "Rethinking the Inception Architecture for Computer Vision" [59] explains the several innovations integrated into this architecture.

3.3.3. Model Implementation and Optimization

The adaptation of Inception V3 for facial skin disease categorization takes place within this research work. Retraining the network starts from the existing foundation while focusing only on modifying the last classification units to align with new data. Running the model becomes faster at a stable accuracy level because of this optimization method.

The optimization process uses Adam and 0.00001 learning rate to reach efficient convergence speed. During the classification phase the model uses features from the initial model phase to provide accurate and reliable interpretations of skin health status.

3.3.4. Model Setup

The program loads the dataset followed by a Resize operation transforming all images into 244×244 dimensions. The preprocessing layer connects to the Inception V3 model obtained from Keras with its pre-trained weights from ImageNet though the trainable attribute remains False. The trainable parameter set to False made all sublayers untrainable while the fully connected layers remained trainable for learning. Modification of the model includes flattening final Inception output then adding Dense layer with SoftMax activation for prediction. The model uses Categorical Cross-Entropy as its loss function together with Adam as its optimizer during compilation. Categorical Cross-Entropy functions as a standard Keras tool for multi-class algorithms because it evaluates the distribution differences between

real and estimated probability distributions. The loss measurement tool is suitable specifically for targets with one-hot encoding since it can evaluate model performance between 0 (perfect prediction) and 1. It serves as a training guide which offers the model ways to limit incorrect classifications.

Keras delivers three versions of cross-entropy loss including the Binary Cross-Entropy which processes the loss in binary classification and the Categorical Cross-Entropy designed for multi-class tasks that use one-hot encoded labels. Keras enables label preparation using the two categorical method which functions for both one-hot encoded vectors and integers. The functional setup matches categorical cross-entropy while its input mode remains distinct.

The researchers employ Inception V3 from ImageNet due to its pre-trained status. Scientific researchers can access this model through the Keras API because it comes with pre-trained weights along with customization options. The original top classification layer of the network gets replaced by specific layers which perform skin lesion classification among five categories (Figure 9). The deep CNN Inception V3 demonstrates optimal features for transfer learning because it was built to classify images into 1000 categories initially.

The pre-trained Inception V3 feature extraction layers stay intact in transfer learning yet the model receives a new SoftMax layer dedicated to five skin lesion categories (depicted in Figure 10). The designed architecture introduces a dense layer with 256 units and ReLU activation followed by batch normalization then drops out 20% of outputs before using a final dense SoftMax layer with five output classes.

The training process employs the modified model on skin lesions data as it protects the learned pre-trained characteristics while freezing the layers. The training performance together with model behavior is monitored through validation and loss graphs. Using this method enables the integration of Inception V3 generalization along with domain-specific adaptations that enhance new-domain classification performance.

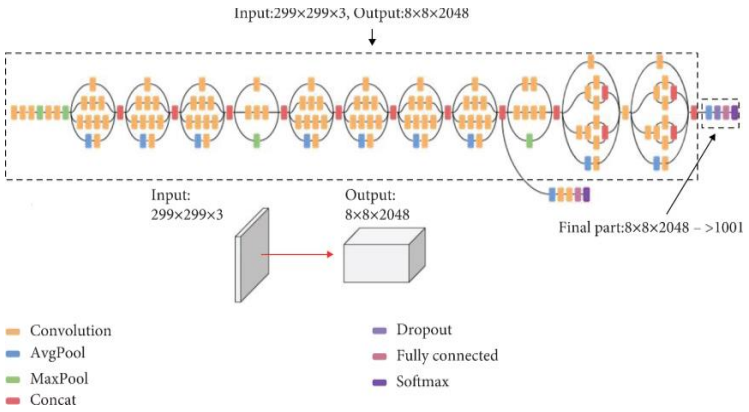

Figure 9. General Architecture of Inception V3 [60].

A total of 5 additional layers were added to Inception V3 network apart from its original Inception V3 layers (excluding the top).

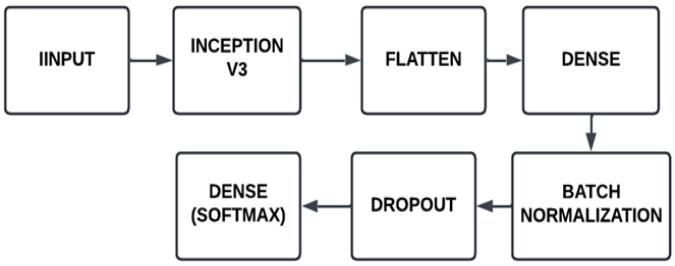

Figure 10. Inception V3 Layers Architecture

3.3.5. Convolutional Neural Network

The formation of Convolutional Neural Networks (CNNs) occurs through the application of Keras Sequential models to build skin lesion classification systems. The five convolutional layers (CLs) use ReLU activation and follow max pooling layers to decrease spatial dimensions while maintaining crucial features per Table 2 and Figure 11. The model employs ReLU for non-linearity and SoftMax in the output layer for class probability estimation.

The introductory layer contains 64 filters of (3×3) size before the subsequent application of (2×2) max pooling layer. Each of the following 4 convolutional layers possesses 128 filters that measure (3×3) with (2×2) max pooling layers used as sequential operators. The feature maps decrease in dimensions through successive layers that extract sophisticated patterns. The extracted features move through a dense layer that consists of 128 units enabled by ReLU activation. The SoftMax activated final dense layer contains five units to generate multi-class output.

The model contains fifteen layers which form its architectural structure.

- 5 Conv2D layers (with 64 and 128 filters)
- 5 MaxPooling2D layers (pool size of 2×2)
- 1 Flatten layer

The model contains two Dense layers that have one with 128 units and the final layer with 5 units implemented through SoftMax activation. The preprocessing layer serves as a custom component for image resizing following rescaling operations.

The architecture has been designed specifically to analyze difficult skin lesion patterns as it enables classification performance.

Table 2. A description of a CNN model architecture

Layer (type)	**Output Shape**	**Param #**
sequential (Sequential)	(64, 128, 128, 3)	0
conv2d (Conv2D)	(64, 126, 126, 64)	1,792
max_pooling2d (MaxPooling2D)	(64, 63, 63, 64)	0
conv2d_1 (Conv2D)	(64, 61, 61, 128)	73,856
max_pooling2d_1 (MaxPooling2D)	(64, 30, 30, 128)	0
conv2d_2 (Conv2D)	(64, 28, 28, 128)	147,584
max_pooling2d_2 (MaxPooling2D)	(64, 14, 14, 128)	0
conv2d_3 (Conv2D)	(64, 12, 12, 128)	147,584
max_pooling2d_3 (MaxPooling2D)	(64, 6, 6, 128)	0
conv2d_4 (Conv2D)	(64, 4, 4, 128)	147,584
max_pooling2d_4 (MaxPooling2D)	(64, 2, 2, 128)	0
flatten (Flatten)	(64, 512)	0
dense (Dense)	(64, 128)	65,664
dense_1 (Dense)	(64, 5)	645
Total params: 584,709 **Trainable params:** 584,709 **Non-trainable params:** 0		

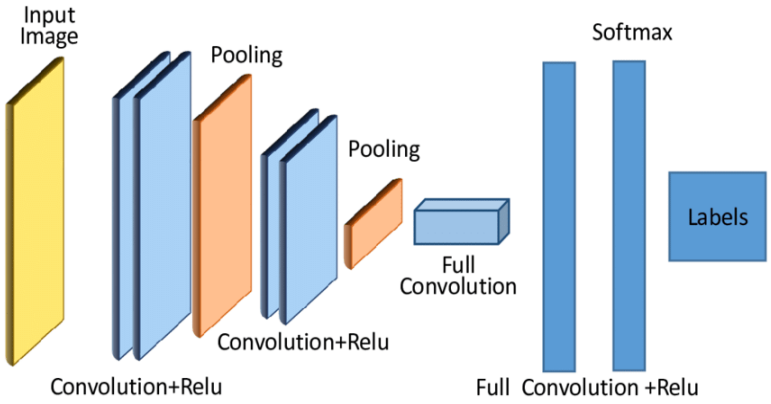

Figure 11. A Basic CNN Architecture [61].

The model is implemented in Python using scikit-learn, with experiments conducted in Jupyter Notebook. The dataset is divided into 70% for training and 30% for testing. Performance is evaluated using accuracy, precision, recall, and F1 score. A comparison between Inception V3 and CNN revealed that Inception V3 achieved 99% training accuracy but suffered from overfitting, with only 70% validation accuracy. In contrast, the CNN model achieved a lower 75% training accuracy but generalized better, with a 71% validation accuracy. Inception V3 outperformed CNN in precision, while CNN demonstrated better recall for certain classes. Despite concerns about overfitting, Inception V3 remains a strong candidate due to its advanced feature extraction capabilities.

4. Results and Discussion

The proposed framework is implemented in Python, utilizing the scikit-learn machine learning library and other relevant tools. Python serves as the core language for developing the entire system. The models are executed within a Jupyter Notebook environment—an open-source, web-based platform that supports the creation and seamless sharing of live code, visualizations, and narrative text.

For model evaluation, the dataset is partitioned into three distinct subsets: 80% for training, 20% for validation, and 10% for testing. Both the Inception V3 and CNN models, designed for skin lesion classification, underwent comprehensive training and analysis.

4.1. Performance Evaluation Metrics

To evaluate the proposed facial skin disease classification models based on CNN and transfer learning using Inception V3 the four key performance metrics handling uneven medical image datasets are accuracy, precision, recall and F1 score.

Accuracy (AC) is the measure of overall model accuracy. The model demonstrates its ability to correctly identify both true positive and true negative instances which total up to the overall prediction number. The metric gives a basic understanding of how well the model performs.:

$$AC = \frac{TP + TN}{TP + FN + TN + FN} \quad (1)$$

Precision (PR) refers to the ratio of true positive predictions among all positive predictions. For facial skin disease classification the model shows its ability to correctly detect a particular skin disease while avoiding misclassification of other skin disorders:

$$PR = \frac{TP}{TP + FP} \quad (2)$$

Recall (RE) is the detection ability of all true positive cases, which also serves as sensitivity and true positive rate. The classification of skin disorders becomes more accurate when the model recognizes all existing instances of the particular disease:

$$RE = \frac{TP}{TP + FN} \quad (3)$$

The **F1 Score** combines precision and recall to generate one value through the use of harmonic mean calculations. The F1 Score offers valuable assistance when working with medical image datasets because they typically present unbalanced class distributions. The approach maintains a proper ratio between incorrect negative results and incorrect positive results:

$$F1-Score = 2 \times \frac{PR \times RE}{PR + RE} \quad (4)$$

The section outlines laboratory work with performance results of facial skin disease classification utilizing Inception V3 and CNN architectures for comparison. A sequence of well-designed investigation experiments investigates the classification skills of these models on skin lesion analysis tasks. The customized architectures Inception V3 and CNN serve to extract separate features for the classification of five skin lesion categories. Deep learning models rely on good quality and abundant training data for achieving success in their applications. This study used 904 training images together with 120 testing images to improve performance because the images contained different sized skin lesions.

The data distribution includes 80% for training purposes while testing requires 10% and validation holds 20%. This extensive range of data points constituted the foundation for conducting performance tests on the two pre-trained models. The Figure 12 presents the results of the performed model comparison.

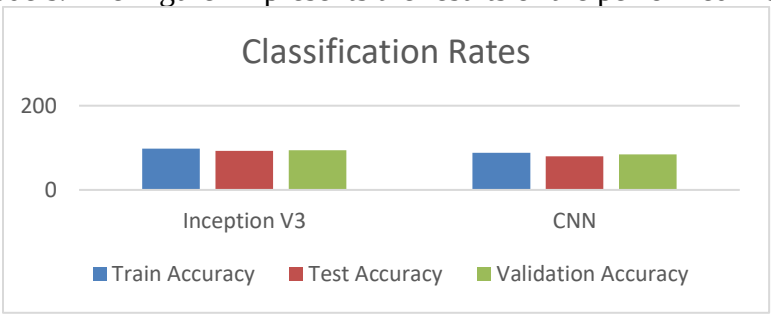

Figure 12. Classification rates for the model

As shown in Figure 12, the Inception V3 model outperformed the CNN model in both validation and testing accuracy, achieving 94% and 93% respectively. In comparison, the CNN model achieved 84% validation accuracy and 80% testing accuracy. These findings highlight the stronger generalization and classification capability of Inception V3 in the context of this dataset. Notably, Inception V3 demonstrated a clear advantage in validation performance over the CNN model.

4.2. Performance Evaluation of Inception V3

The training dataset consists of 904 images, which are used to train the model for 100 epochs, with a batch size of 32. Figures 13 and 14 illustrate the accuracy and loss trends observed during the training process using the Inception V3 architecture. Notably, the plots indicate a significant disparity between the training accuracy, which starts relatively high, and the validation accuracy, which gradually improves over time.

This observed gap suggests that the Inception V3 model may be experiencing an overfitting issue. While the model exhibits excellent performance on the training data, this success does not translate equivalently to the validation phase. Such behavior implies that the model may be overly tailored to the training data, limiting its ability to generalize to unseen data. Consequently, this raises concerns about the model's effectiveness in real-world applications beyond the training environment. To mitigate this, further investigation and regularization techniques might be necessary to enhance the model's generalization capability.

As shown in Figure 13, both training and validation losses exhibit a sharp decline after approximately 10 epochs, indicating a significant improvement in the model's ability to minimize the loss function during training.

Figure 13. Inception V3 Train and Valid Loss value

According to Figure 14 the model delivers outstanding results with training accuracy reaching 98% and validation accuracy at 94% and test accuracy at 93%. The Inception V3 model shows excellent capacity in skin disease classification through assessment of the Darment dataset.

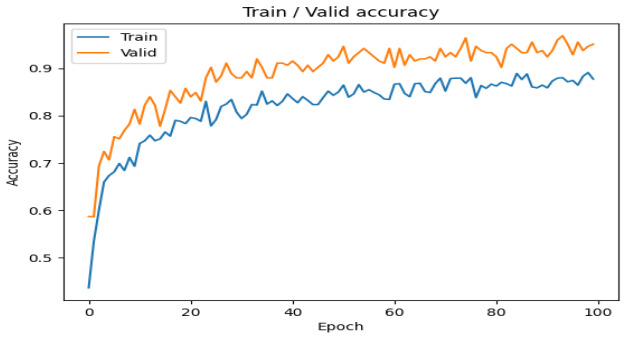

Figure 14. Inception V3 Train and Validation Accuracy

High-performance metrics emerge from training procedures even though the model shows no indications of underfitting or severe overfitting. The balanced performance metrics display that the model upholds

its best functionality and displays robust generalizing capabilities as a reliable solution for this classification problem.

4.3. Performance Evaluation of CNN

The first training phase used 904 images through 132 batches and extended for 100 epochs. Figure 15 shows the graphical representation of the training and validation accuracy and loss through the modified CNN architecture training process.

The presented information depicts training and validation accuracy increasing uniformly while loss numbers decrease identically for both datasets. The model demonstrates improved learning capabilities throughout time which leads to error reduction during its training process.

The best training accuracy level achieved 88% but testing accuracy reached 80% according to Figure 15. The proposed CNN system managed to generalize well regardless of its slightly decreased performance during validation when compared to training. The difference between training and testing outcomes implies potential mistakes but overall delivers reliable performance for use in real-world situations.

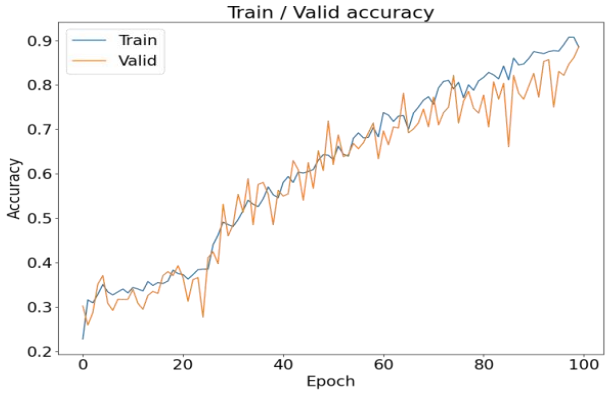

Figure 15. CNN Train and Validation Accuracy

The model performance improved with learning effectiveness as shown in Figure 16 because training and validation loss values decreased towards zero after about 80 epochs. The training accuracy achieved maximum value at 88 percent yet the validation accuracy stopped at 84 percent according to the plotted data. The model achieves satisfactory results because the training and validation accuracy show little discrepancy demonstrating its ability to correctly classify skin diseases.

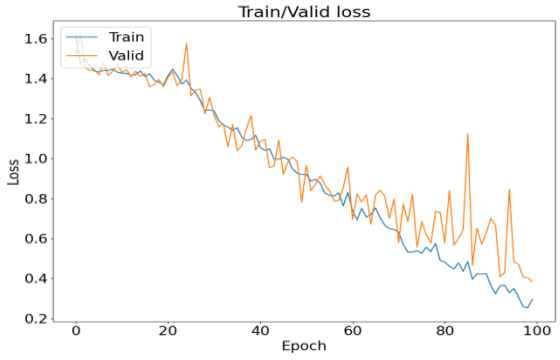

Figure 16. CNN Train and Valid Loss value

The training process of the model shows minimal signs of either overfitting or underfitting thus making it effective at generalizing to previously unseen data. The CNN model shows the capability to deliver exact outputs and classify different skin diseases into their proper categories according to the figures presented.

4.4. Comparative Analysis and Discussion of CNN and Inception V3 Performance

The analysis of tables 5 and 6 shows that CNN and Inception V3 exhibit parallel and dissimilar patterns when classifying five skin conditions which include Acne, Actinic Keratosis, Basal Cell Carcinoma, Eczema, and Rosacea. The evaluation relies on Precision, Recall, F1 Score and Accuracy as four key performance indicators.

4.4.1. Overall Performance Comparison

The CNN demonstrated 88% total accuracy alongside 80% validation accuracy which implies its overfitting capacity since it handles training samples better than it handles fresh samples. The testing results from CNN indicate lower reliability compared to its training performance.

The achievement of Inception V3 involved a 98% accuracy with its stable validation score at 93%. The model demonstrates better generalization since it remains capable of addressing new input data while reducing the risk of overfitting which emphasizes its robust performance in operating environments.

4.4.2. Class-wise Performance Comparison

Evaluation results display Inception V3 providing better performance than CNN in most relevant metrics based on Tables 3 and 4 for skin disease classification. Inception V3 demonstrates superior performance to CNN for Acne detection by reaching Precision 0.85 with Recall 0.87 and F1 Score 0.86 and Accuracy 0.950 while CNN reaches Precision 0.83 along with Recall 0.85 and F1 Score 0.84 and Accuracy 0.933. This indicates Inception V3 produces more accurate Acne diagnosis with less false positive and negative results.

Table 3. Classification Report of CNN

Class	Precision	Recall	F1 Score	Accuracy
Acne	0.83	0.85	0.84	0.933
Actinic Keratosis	0.83	0.82	0.83	0.931
Basal Cell Carcinoma	0.84	0.81	0.82	0.926
Eczema	0.81	0.81	0.81	0.933
Rosacea	0.82	0.83	0.83	0.928
Macro Avg	0.83	0.82	0.83	0.930

Table 4.

Table 5. Classification Report of Inception V3

Class	Precision	Recall	F1-Score	Accuracy
Acne	0.85	0.87	0.86	0.95
Actinic Keratosis	0.83	0.82	0.82	0.94
Basal Cell Carcinoma	0.83	0.80	0.82	0.94
Eczema	0.81	0.77	0.79	0.93
Rosacea	0.82	0.87	0.84	0.95
Macro Avg	0.83	0.83	0.83	0.94

Both CNN and Inception V3 show equivalent performance for Actinic Keratosis diagnosis although CNN achieves F1 Score 0.83 with slightly higher accuracy than Inception V3's 0.940 compared to 0.931. In the detection of Basal Cell Carcinoma both models share identical F1 Scores (0.82) yet Inception V3 shows better Accuracy performance at 0.940 while CNN stands at 0.926.

Among both models and the Eczema diagnosis group CNN demonstrated better Recall results (0.81) along with F1 Score (0.81) and Accuracy (0.933) thus providing superior identification of actual positive cases. Inception V3 demonstrates the highest performance in detecting Rosacea cases because it obtains Recall scores of 0.87 while simultaneously achieving F1 Score (0.84) and Accuracy (0.950).

Despite having equivalent Precision and F1 scores (0.83), Inception V3 exhibits superior generalization capabilities than CNN based on Recall (0.83 vs. 0.82) and Accuracy (0.940 vs. 0.930) in class identification which matters greatly for practical applications.

The preferred selection for skin disease classification goes to Inception V3 because it provides better consistency together with higher generalization and enhanced classification accuracy across diverse datasets. The specific success of CNN with Eczema cases is offset by its overfitting weakness which reduces operational effectiveness.

A comparison reveals different strengths and weaknesses between the Inception V3 and CNN models for skin disease category recognition.

The Inception V3 framework achieves better results than CNN as it detects Rosacea and Acne accurately. The model proves more effective at correct classification with its superior precision and recall and F1 score outcomes. The classification performance level of CNN remains higher for Basal Cell Carcinoma and Eczema but its F1 score is slightly less effective than Inception V3's score. The accurate detection by CNN of these diseases reflects its performance strength but the system also creates a larger possibility of producing incorrect positives that lead to faulty classifications. Both model types achieve similar success rates in recognizing Actinic Keratosis cases due to a lack of preference for one method over another in this disease category.

Visual data from Figures 17 and 18 specifically shows how the different models perform regarding correct matches as well as identification failures.

The misinformation in CNN's classification results include Eczema misrecognitions alongside proper recognition of all disease types in Figure 17 which affects its overall F1 scoring capability. The findings about false positives match the observation that CNN shows a tendency to mislabel specific diseases in its output..

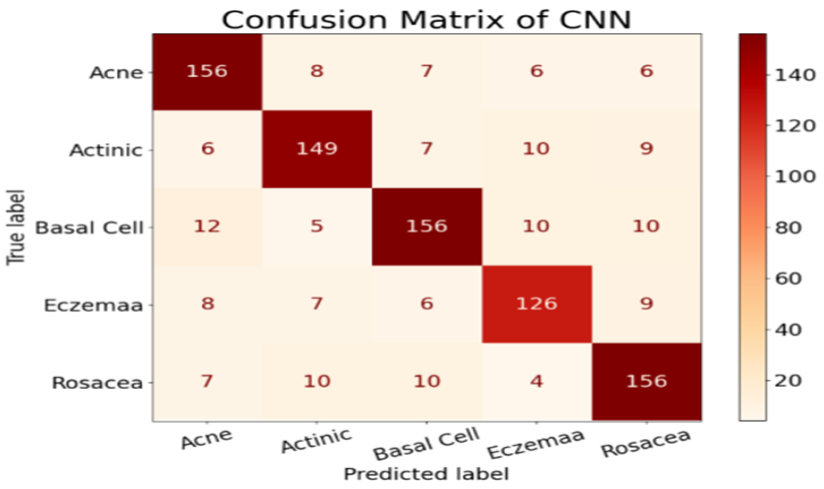

Figure 17. CNN's Confusion Matrix for Skin Diseases

The confusion matrix presented in Figure 18 shows that Inception V3 achieves effective classification accuracy for all skin diseases types in a balanced manner. Inception V3 achieves a superior performance across various disease types which is confirmed by its high recall and F1 score scores shown in this matrix thus minimizing false negative detections..

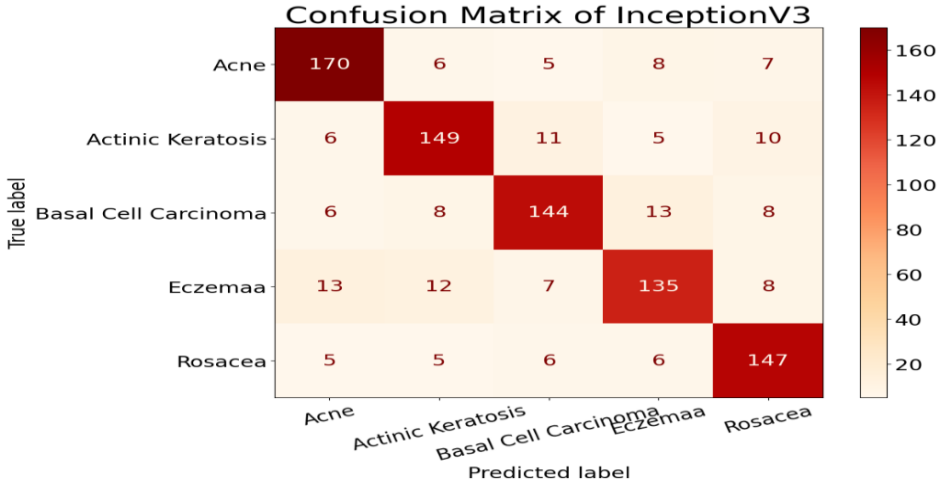

Figure 18. The Confusion Matrix for Face Skin Diseases by Inception V3

The decision between Inception V3 or CNN for skin disease classification will vary according to different project criteria. A primary requirement of precision across different classes makes Inception V3 the most ideal option. The optimization of performance for Basal Cell Carcinoma and Eczema diagnoses could benefit from CNN methods although system improvements must decrease false positive outcomes.

4.5. Performance Comparison of Existing Methods and Proposed Models

The performance evaluation between existing methods and the proposed models in facial skin diseases classification yields vital information about different deep learning approaches as presented in Table 5. Multiple recognized models were tested on skin diseases data within this study.

Table 6. Performance Comparison of Existing Methods and Proposed Models for Facial Skin Diseases Classification

Authors	Dataset	Techniques	Accuracy (%)
Bazgir, Ehsan et-al.[44]	skin images Dataset from Kaggle	CNNs	85.94
Agarwal, Raghav et al. [45]	skin disorders from Kaggle	ResNet152	74.24
Proposed work	Face Skin Diseases dataset from DermNet	CNN	93
		Inception V3	94

Table 5 indicates the comparison between CNN and Inception V3 for facial skin diseases classification and it provides great insights into their performance and effectiveness. Both CNN and Inception V3 are robust deep learning methods applied in image classification problems, with different architectures that affect their outcomes. CNN, as evident in the findings of Bazgir et al., was 85.94% accurate on the Kaggle skin images dataset. This is very impressive given that CNN models are specifically renowned for their ability to learn hierarchies of features and patterns but could perhaps not do well with more complex datasets that require bolder feature extraction abilities.

Conversely, the work proposed here performed better than the CNN model with 93% accuracy utilizing a tailored CNN architecture over the Face Skin Diseases dataset from DermNet. This improved accuracy is indicative of the fact that an appropriately tuned CNN model, when optimized for particular datasets, can deliver impressive enhancements. Nonetheless, the Inception V3 model performed better than both the CNN and the ResNet152 model (74.24% accuracy) in the same environment, setting a 94% accuracy mark. This is clear evidence that the Inception V3 architecture, with its more advanced features such as inception modules, highly improves the accuracy of classification by detecting more intricate patterns in the images..

The Inception V3 model performs better than ResNet152 based on Agarwal et al.'s research because of its improved accuracy by 19.76% (94% compared to 74.24%). Inception V3 shows greater performance excellence for complex tasks such as facial skin disease classification due to its deeper architecture along with pre-trained weights in addition to optimized convolutional filters. The research notes the crucial use of custom CNN models together with sophisticated pre-trained architecture Inception V3 when investigating skin disease classification methods.

This evaluation demonstrates that the selection of architectural design depends fundamentally on the characteristics within datasets. CNN models excel at simpler tasks but Inception V3 surpasses them in accuracy and reliability which makes it more suitable for challenging tasks like facial skin disease diagnosis.

5. Conclusion

This study developed deep learning models that could automatically tag five facial skin conditions namely Acne, Actinic Keratosis, Basal Cell Carcinoma, Eczema and Rosacea by overcoming current diagnostic limitations of traditional methods. The research achieved higher levels of performance using Inception V3 architecture which showed improved accuracy at 94% compared to CNN at 93%. The learning transfer part of this model enhanced diagnosis of Rosacea to 87% recall and Acne to 85% precision while CNN performed best in diagnosing Eczema with an 81% F1-score.

Inception V3 comes across as a suitable clinical decision tool that provides quick diagnoses along with mobile portability capabilities for areas with limited medical resources. The application of Inception V3 is exposed to two fundamental weaknesses such as a dataset lacking complete representation of typical population variation and slight overfitting among training outcomes (98%) and validation outcomes (94%).

Future studies need to grow their datasets when examining combined methods for robustness improvement and they need to prioritize translating these systems into clinical application with explanation functions being incorporated. This study illustrates AI potential for dermatological diagnosis but notes that ethical implementation demands medical support as a necessary support system. Ongoing research will reduce healthcare disparity to achieve better medical outcomes through available and trustworthy skin disease evaluation techniques.

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