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Skin Disease Classification and Detection Using Deep Learning

Arthy Rajakumar[1*], Deepa Priya. V[2], P. Priyadharshini[3], R. Muthulakshmi[4]
[*1]Assistant Professor, Department of Information Technology, Kamaraj College of Engineering and Technology, S.P.G.C. Nagar, K.Vellakulam-6257001, India. Email: arthyit@kamarajengg.edu.in
[*2]Assistant Professor, Department of Information Technology, Kamaraj College of Engineering and Technology, S.P.G.C. Nagar, K.Vellakulam-6257001, India. Email: deepapriyait@kamarajengg.edu.in
[*3]Assistant Professor, Department of Information Technology, Kamaraj College of Engineering and Technology, S.P.G.C. Nagar, K.Vellakulam-6257001, India. Email: priyadharshiniit@kamarajengg.edu.in
[4]Department of Computer Science, The Standard Fireworks Rajaratnam College for Women, India
E-mail: muthulakshmi032002@gmail.com

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Abstract
The integumentary system is a remarkable component of the human anatomy, frequently susceptible to an array of recognized and unrecognized maladies. There exists a multitude of prevalent disorders, some of which rank among the most ubiquitous globally. The identification of these ailments can present challenges due to disparities in cutaneous consistency, the presence of follicles, and variations in pigmentation. Furthermore, in remote regions with limited access to medical facilities, individuals may disregard initial symptoms, thereby exacerbating their conditions progressively. The diagnosis of dermatological conditions may also prove to be considerably time-intensive. The implementation of machine learning techniques is imperative for enhancing the precision of diagnostic procedures for diverse skin afflictions. Deep learning methodologies, commonly utilized in medical domains, scrutinize image feature parameters to render diagnostic determinations. This progression encompasses three primary phases: feature delineation, model training, and evaluation, leveraging machine learning algorithms to assimilate insights from an assortment of dermatological images. The primary objective is to amplify the accuracy of detecting skin diseases through this computational framework. The proposed system incorporates the Convolution Neural Networks (CNN) for efficient classification and detection of the skin diseases. CNNs have demonstrated unparalleled efficacy in tasks pertaining to visual perception. The endeavor at hand involves the formulation of a CNN classifier utilizing Python, with Keras and Tensor Flow as the underlying computational tools. The exploration of diverse network configurations will entail the assessment of various layer types, including Convolutional, InceptionV3, Dense, and Pooling layers. This envisioned system attains a peak accuracy level of 90% within this specified model.

Keyword: *Dermatology, Convolutional Neural Network, Confusion Matrix, Machine Learning*

1. INTRODUCTION

The human skin is unparalleled in size, covering an expansive area of more than 20 square feet, making it the body's largest organ. Comprised of three layers—the hypodermis, dermis, and epidermis—each layer boasts unique functions and anatomical traits. Beyond its sheer dimensions, the skin operates as a sophisticated barrier, acting as the body's primary defence against a multitude of external threats, ranging from viruses and UV rays to toxins and physical trauma. Furthermore, the skin's intricate network contributes significantly to the regulation of body temperature and moisture levels, ensuring optimal internal balance. While skin cancer, particularly melanoma, is a significant cause of mortality, there's a general increase in the prevalence of skin disorders. These conditions not only affect the skin but also have implications for a person's daily life. It makes someone feel less confident, which ruins relationships and sends them into sadness. Skin conditions can afflict people of various ages.

In 2023, an estimated 1.8 billion people worldwide will experience a skin condition. There have been about 232,000 reported cases globally, emphasizing the importance of early detection for better survival rates. Figure

1 shows the skin's three primary layers: the epidermis, dermis, and hypodermis. Each year, around 5,000,000 new cases of skin cancer, which can be divided into melanoma and non-melanoma types, are diagnosed in the United States, posing a significant public health concern.
Ongoing endeavours focus on creating a skin disease detection model using Convolutional Neural Networks (CNNs) in Python, utilizing Keras and TensorFlow. Exploring various network structures, like convolutional, dropout, pooling, and dense layers, these will be assessed using a dataset obtained from the International Skin Imaging Collaboration (ISIC) archives. [2]
The aim is to save lives by detecting skin diseases early. The proposed system is designed to be straightforward, quick, and affordable.

1.1Need and Motivation

Early detection and treatment of skin diseases can lead to recovery rates exceeding 95%. Therefore, identifying these conditions in their initial stages is crucial to prevent their spread and achieve successful treatment outcomes. The proposed system may benefit for the following reasons:

- Skin Disease Detection at No Cost
- Enhance Diagnosis Speed
- Frequently, Skin Diseases Misdiagnosed Due to Limited Knowledge
- Global Accessibility for Productive Use
- Utilize Free Tools for Deployment
- Simplified Maintenance

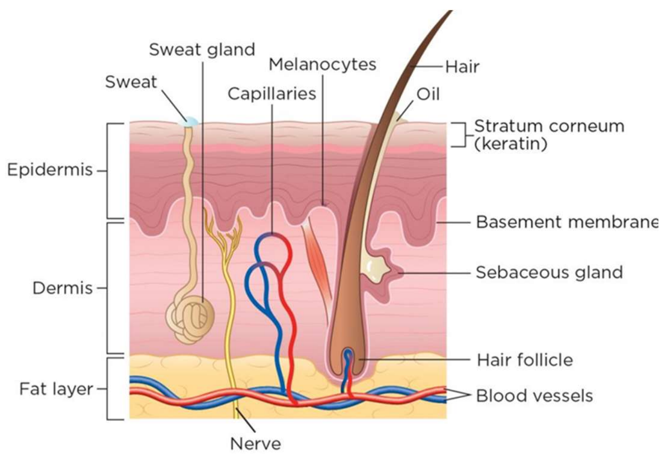

Figure 1 Structure of human skin

2. LITERATURE REVIEW

Skin problems, including fungal, bacterial, viral, and allergic origins, are prevalent and can alter skin appearance and texture. Chronic skin infections, if left untreated, may progress to skin cancer. Early detection is crucial to halt their advancement. Delayed diagnosis and treatment of skin ailments can be costly and physically taxing for patients. Researchers have extensively studied images of skin conditions to devise diagnostic methods. This section explores skin disease detection techniques as outlined in Table 1, presented in detail.

Table 1 Summary of Previous Research

Problem Statement	Method Used
ML approach for skin disease detection and classification [3]	SVM, KNN Decision Tree for image. Classification
An efficient mechanism to detect skin disease using SVM [4]	SVM K-Means clustering GVF – Gradient Vector Flow
Leaf and skin disease detection using Machine Learning [5]	Employing image processing to identify the diseased region and utilizing multi-class SVM and GLCM for classification purposes.
Intelligent System for Skin Disease Prediction using ML [6]	Applying Support Vector Machine (SVM) and Convolutional Neural Network (CNN) machine learning algorithms.
ML algorithm-based skin disease detection [7]	Five distinct machine-learning algorithms, namely Logistic Regression, Kernel SVM, Random Forest, Naïve Bayes, and Convolution Neural Network, were utilized.
A method of skin disease detection using Image processing and ML [8]	Utilizing dermoscopic images to extract features and employing convolutional neural networks for classification.
Deep Learning based skin disease classification [9]	Deep Learning Network
Skin disease classification using ML and DL models [10]	CNN, SVM, Decision tree, and Light Gradient algorithms are used.
Skin disease detection using ML and DL [11]	AI, GLCM, SVM, CNN, and KNN algorithms are used.
Skin disease detection using ML and DL [12]	SVM, CNN, Bayesian, Fuzzy c-means Inception v3, and random forest algorithms are used
skin disease detection using Machine Learning [13]	Using VGG 16, Dense Net, and CNN
A model for classification and diagnosis of ML and Image Processing techniques [14]	Using SVM, KNN, Random Forest
Detection and classification of skin disease[15]	Using CNN, Inception-v3 AlexNet And ResNet152v2
Skin Detection Using Machine Learning [16]	SVM, KNN, Naïve Bayes
A novel skin disease detection technique using ML [17]	SVM, KNN, ANN
Skin disease detection using ML [18]	CNN
Skin disease detection using ML and DL [19]	Using deep learning techniques such as Keras, TensorFlow, Angular JS, and chatbot integration
Identification of skin disease using Machine Learning [20]	K-Means for image segmentation SVM, KNN
The smart detection and analysis on skin tumor disease using bio-Imaging deep learning algorithm[24]	Bio imaging,AI,CNN,PCA,MDS,ANN,K-Mzeans
A comparative analysis of single and combination feature extraction techniques for detecting cervical cancer lesions[25]	GLCM
Comparative analysis of Genetic algorithm[26]	SVM, CNN
Classifying benign and malignant masses using statistical measures [27]	CNN

Research shows that these methods have the potential to diagnose different skin conditions. Using deep learning, especially in CNNs, has greatly improved performance and accuracy. However, challenges like imbalanced datasets, understanding how the models work, and dealing with misidentified cases need to be solved to make skin disease detection systems more widely used and trusted.

The subsequent sections of the paper are structured as follows: Section 3 presents background information, Section 4 describes model validation, Section 5 presents result analysis, and Section 6 serves as the conclusion.

3. BACKGROUND DETAILS

3.1 Main Text

Skin conditions impact approximately one-third of the world's population, creating a significant healthcare challenge. Deep learning offers a potential solution by leveraging neural networks to analyse skin images and optimize healthcare workflows.

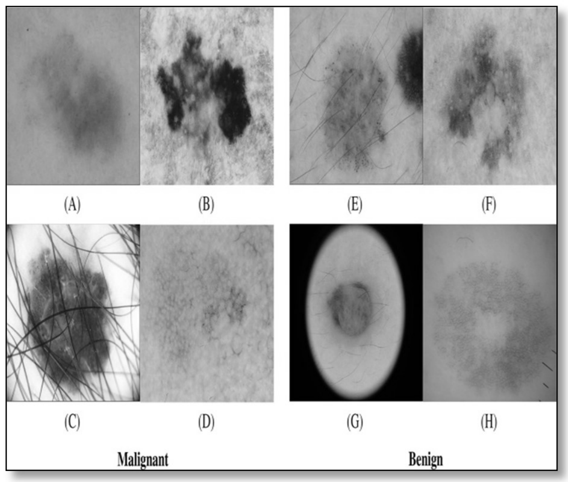

Figure 2 Different Skin Lesion examples in the ISIC 2017 dataset.[21]

3.2Methodology

Doctors harness the power of deep learning and neural networks to distinguish between benign (like moles and seborrheic keratosis) and malignant (like melanoma) skin conditions, thereby enabling swift diagnosis and timely treatment. This diagnostic journey commences with categorizing skin diseases using photographic imagery, utilizing the TensorFlow framework in Python for execution. Deep learning methodologies, renowned for their adeptness at recognizing intricate patterns within data, are pivotal components of this framework. Through meticulous analysis of image attributes such as color, texture, and morphology, the model acquires the capability to discern between diverse skin ailments. Extensive training on comprehensive datasets empowers the model to accurately classify unseen images with precision. Subsequently, the model serves as an invaluable aid to dermatologists by furnishing automated assessments of skin images, expediting diagnostic procedures and ensuring accuracy. The integration of deep learning into the realm of skin disease detection marks a significant leap forward in healthcare technology, bolstering diagnostic precision and facilitating prompt interventions for enhanced patient outcomes.

Architecture of Proposed System

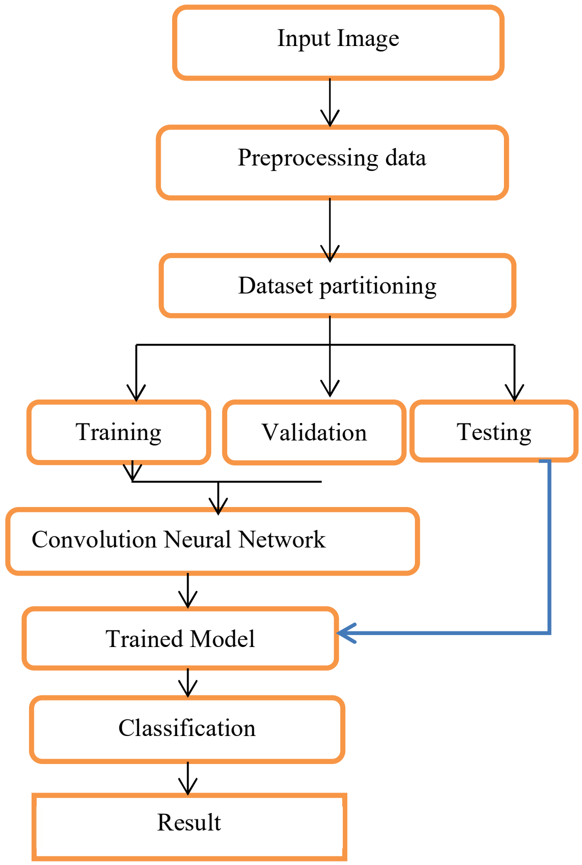

Figure 3 The Proposed System Architecture.

The model is run through a sequence of steps.

3.2.1 Data Gathering:
The ISIC 2017 dataset is gathered from the website https://www.isic-archive.com/ for collecting data.

3.2.2 Data Pre-processing:
a. cache(): To save the pre-processed dataset to a local cache file, it will only pre-process the data once, during the first epoch of training.
b. shuffle(): To mix up the dataset, the samples are put in a random order.
c. repeat(): The dataset will keep producing samples continuously, which is helpful for training.
d. batch(): The dataset is split into batches of 64 or 32 samples for each training step.
e. prefetch(): This function fetches batches in the background while the model keeps training.

3.2.3 Model Building:
a. InceptionV3
b. ImageNet
c. Binary Classification.

Inception V3
Inception V3 (Figure 4) is a pre-trained model initially trained on the ImageNet dataset, containing over a million images across 1,000 classes, using powerful computational resources. The model's ability to retrain its final layer allows for retaining previously learned knowledge and applying it to smaller datasets, resulting in accurate classifications without extensive training or computational demands. This approach not only saves

time and resources compared to training from scratch but also benefits from the model's understanding of general image features. Leveraging transfer learning with Inception V3 enables researchers and developers to efficiently classify skin diseases using the model's pre-existing knowledge and expertise, thus improving diagnostic accuracy and reducing the need for vast amounts of labeled data.

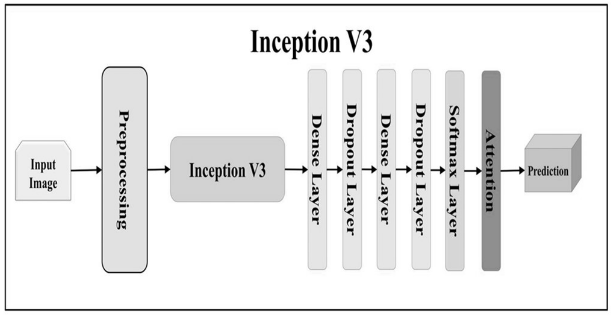

Figure 4 Inception v3 architecture.

Imagenet

The ImageNet project is a pivotal resource in the realm of visual object recognition software research, providing a vast and meticulously labelled database. Its primary purpose is to serve as a benchmark for evaluating the efficacy and advancements of various visual recognition algorithms, thereby fostering continuous innovation and progress in the field of computer vision. ImageNet, with its vast array of labelled images across a wide range of object classes, is instrumental in the creation and improvement of powerful machine learning models, such as the advanced Inception V3 deep neural network. By utilizing ImageNet's extensive dataset and benchmarking tools, researchers and developers can significantly boost the accuracy and efficiency of visual recognition systems, thereby advancing technology and its applications in numerous fields. [23]

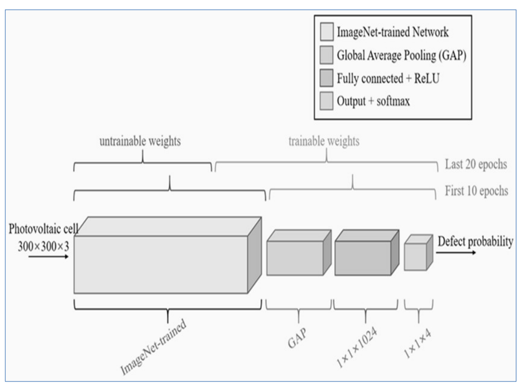

Figure 5 ImageNet Architecture

Binary Classification

Binary classification, a core concept in machine learning, is essential for image classification tasks. In these tasks, skin images are categorized into one of two classes: normal or abnormal. In the medical domain, binary classification aids in diagnosing skin diseases such as melanoma or benign nevi based on image features, contributing to early detection and improved patient outcomes.

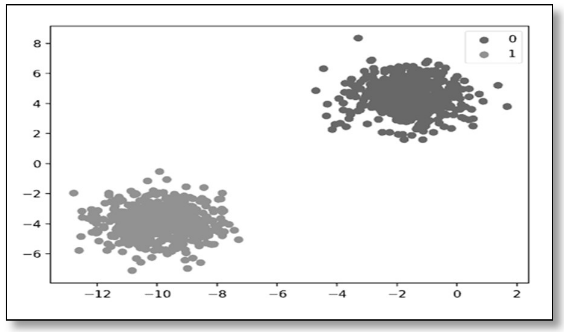

Figure 6 Binary Classification

3.2.4 Model Training:

Train both the CNN and InceptionV3 models using the training set, specifying the batch size and number of epochs.

CNN

Convolutional Neural Networks (CNNs) are multi-layered neural networks designed with a specialized architecture to identify complex features in input data. The fundamental structure of a CNN is illustrated in Figure 7.

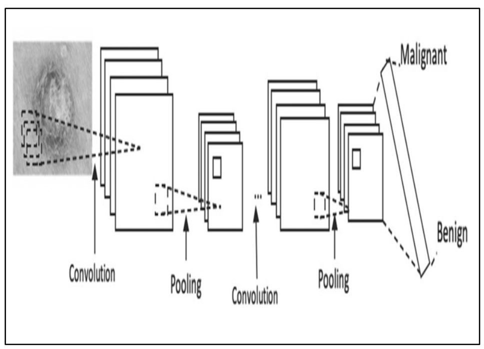

Figure 7 Basic CNN Architecture

At the core of the CNN model lie three key layers:

- Convolutional: Image feature extraction.
- Fully connected: Dense neural connections.
- Pooling: Down sampling spatial dimensions.

Convolutional Layer:

The convolutional layer, crucial in CNNs, applies filters to input images, computing the dot product between the image's pixel matrix and the kernel. This process creates a feature map.

Fully Connected Layer:

Each neuron in the layer above and below is connected to every neuron in this layer. The fully connected layer (FC) plays a crucial role in mapping input to output. It receives flattened input from preceding layers and passes it through additional FC layers, ultimately leading to the classification stage.

Pooling Layer:

The pooling layer typically follows a convolutional layer and aims to decrease the size of the convolved feature map. Max Pooling extracts the highest value from the feature map, while Average Pooling calculates the mean value of elements in a defined region of the image.

3.2.5 Model Evaluation:

Appraise the model's performance using suitable metrics with the validation data.

3.2.6 Model Prediction:

Implement methods for interpreting the model's predictions.

4. MODEL VALIDATION

Dermatological research extensively evaluates ML and DL models through a set of standardized metrics, including accuracy, sensitivity, specificity, confusion matrix, and ROC AUC. The definition of the mentioned parameters is presented below:

- **True positives (TP):** Samples correctly identified as positive.
- **True negatives (TN):** Samples accurately predicted as negative.
- **False positives (FP):** Instances erroneously labelled as positive.
- **False negatives (FN):** Samples inaccurately forecasted as negative.

4.1 Accuracy:

Accuracy denotes how closely measured or calculated results align with the true or expected values, reflecting the reliability of the outcomes.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \qquad (1)$$

4.2 Sensitivity:

Sensitivity is determined by considering the number of individuals who have the disease, rather than the entire population.

$$Sensitivity = TP / (TP + FN) \qquad (2)$$

4.3 Specificity:

Specificity is calculated by assessing the quantity of individuals who do not have the disease.

$$Specificity = TN / (TN + FP) \qquad (3)$$

4.4 AUC ROC:

AUC ROC represents the area beneath the Receiver Operating Characteristic curve. The ROC curve displays how effectively a classification model separates classes, using TPR and FPR. Higher TPR signals better sensitivity, while lower FPR suggests better specificity. AUC summarizes the model's performance overall, where 1.0 means perfect classification and 0.5 means random guessing. In this case, the model achieves an AUC ROC of 0.671.

4.5 Confusion Matrix:

A confusion matrix presents a summary of predictions in a matrix format, detailing the correctness and incorrectness of predictions for each class. It aids in identifying classes that the model confuses with others.

		Actual class	
		P	**N**
Predicted class	**P**	**TP**	FP
	N	FN	**TN**

Figure 8 Confusion Matrix

5. RESULT ANALYSIS

The use of deep learning in identifying skin diseases offers a promising avenue for precise and effective diagnosis. This section presents the outcomes of employing this system. The InceptionV3 model was trained with 2,750 images from the ISIC 2017 dataset. Of these, 70% (2,000 images) were used for training, 10% (150 images) for validation, and the remaining 20% (600 images) for testing. The skin disease prediction networks output layer identifies two classes: Melanoma, and benign. The parameters proposed in this system are tabulated in Table 2. The skin disease sample test images are displayed in Figure 9.
This system conducted a sensitivity evaluation to evaluation the robustness of the model to change the input data.

Table 2 Parameters proposed in this system

Parameter	Description
Input Image Size	299 x 299
Batch Size	64
Figure Size	12 x 12
Model	Sequential
Final Layer	Softmax
Threshold Value	0.5
Trainable Parameters	2,049
Total Parameters	2,18,04,833

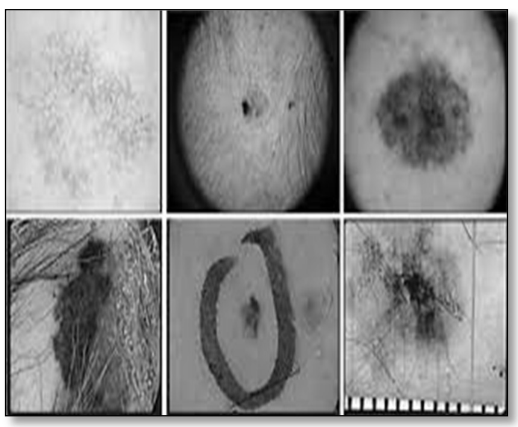

Figure 9 Skin disease Test Images

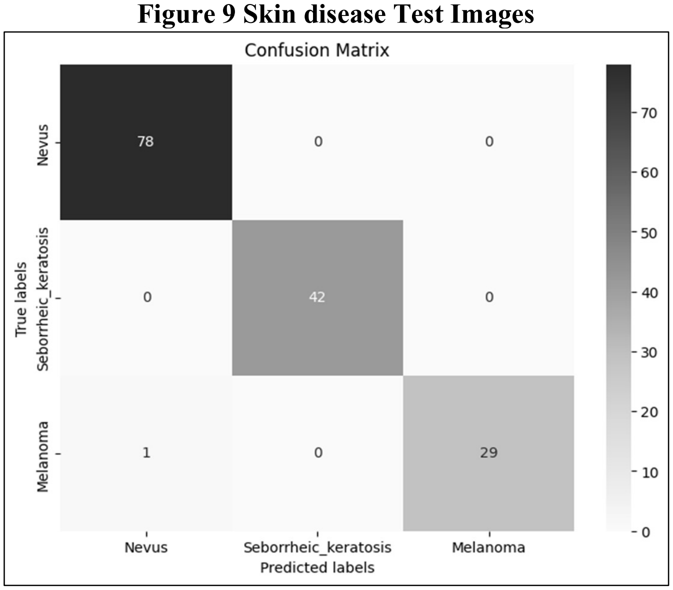

Figure 10 Confusion Matrix of CNN Model

The model evaluation for our Train and Test model is as follows:

Table 3 Model evaluation of the proposed system

Metrics	Value Obtained	
	Train Model	Test Model
Accuracy	80 %	90 %
loss	49 %	28 %
Recall	90 %	90 %
Precision	30%	32%
AUC ROC	0	0.616

This proposed system produces the highest accuracy with 90 % in this model.
The true positive rate (TPR) and the false positive rate (FPR) are key metrics for determining the area under the ROC curve. An AUC of 1 indicates a perfect model in every scenario. In this case, the model achieves an AUC ROC of 0.671.

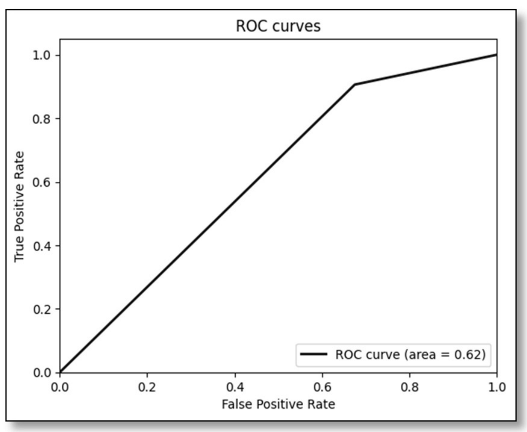

Figure 11 ROC AUCs for the proposed model

6. CONCLUSION

The skin is the body's largest natural component, serving as a crucial barrier against environmental threats. Skin ailments can arise due to various internal and external factors, making the diagnosis of skin diseases a crucial aspect of medical science. Effective diagnosis can significantly reduce mortality rates associated with skin conditions and infectious diseases. This study explores the feasibility of constructing a universal skin disease classification system using CNN and InceptionV3. The research achieves a remarkable 90% accuracy with minimal loss and enhanced sensitivity.

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