A Transfer Learning-based Pre-trained VGG16 Model for Skin Disease Classification

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***Abstract*— Skin disorders pose a significant global health risk, impacting millions of individuals and placing a substantial burden on healthcare systems. The accuracy and speed of diagnosis are crucial for effectively managing various conditions. Deep learning models have demonstrated exceptional performance in diverse medical imaging applications, including the categorization of skin diseases. In recent years, the VGG16 deep learning architecture has gained prominence for its ability to extract meaningful features from images. In this study, a VGG16 model has been leveraged to early diagnose skin diseases. This approach involves collecting an extensive dataset comprising images of different skin disorders sourced from an open-source repository "Kaggle". Further, the VGG16 model is then fine-tuned on this collected dataset to learn the distinguishing patterns and characteristics associated with different skin conditions. The evaluation of the model's effectiveness has been done using standard metrics such as precision, recall, F1-score, and accuracy. These metrics assess the model's analytical capabilities in distinguishing between various skin disorders. The proposed deep learning model achieves remarkable accuracy of 90.1%, proving its proficiency in diagnosing a wide range of skin diseases, including those that appear similar. Furthermore, precision, recall, and F1-score have been identified as 0.867, 0.942, and 0.891, respectively. This research contributes to the evolution of computer-aided disease detection, potentially leading to enhanced healthcare outcomes by facilitating early detection and treatment of skin disorders. Nonetheless, continuous refinements and validation on larger, more diverse datasets are imperative to further enhance the model's accuracy and ability to generalize across various conditions.**

Keywords: Machine Learning (M.L), Skin Diseases, Deep learning (D.L), CNN, VGG16 Model,

I. INTRODUCTION

Skin diseases have a substantial global health impact, affecting millions of people globally. Skin is considered as one of the protecting parts for safeguarding the internal organs. Skin diseases are serious problems leading to rashes, cancer, and inflammation. The correct and timely diagnosis of skin disorders is critical for optimal treatment and management [1][2]. Skin Diseases, often known as dermatological disorders or skin problems with a broad category of medical conditions affecting the skin. Examples of skin diseases include acne, atopic dermatitis, shingles, hives, contact, dermatitis, etc. [3]. The treatment of skin disease is required to be done on time, if not then it can be transferred from one person to another and can also damage other body parts. The identification of skin diseases is challenging due to the general public's lack of medical expertise and the need for costly laboratory tests. Artificial intelligence and deep learning breakthroughs have changed the medical industry in recent years, providing creative solutions to different disease diagnoses. Convolutional Neural Networks (CNNs) have emerged as robust tools for image identification tasks, displaying great performance in medical imaging analysis, particularly skin disease diagnosis[4]. The severity of these diseases and their causes, symptoms, and therapies might vary. Different types of skin diseases have been observed around the world such as vitiligo skin, eczema etc. Various skin diseases can be treated by taking home remedies. However, with the advancements in these diseases, it becomes difficult to treat them. Further, the tests for such disease identification are time-consuming and expensive. The deep learning models can be used in the early prediction of skin diseases which may lead to reducing time complexity and expensive tests. The proposed study uses a pre-trained VGG16 model which is based on conventional convolutional neural networks for image classification. This model analyzes the skin disease images and extracts the essential features and further classifies their outcomes in the form of skin diseases. Human health may be jeopardized if the decision is incorrect or delayed [5]. Therefore, it becomes important and required to create effective methods for identifying and diagnosing skin disease signs at their earliest stages.

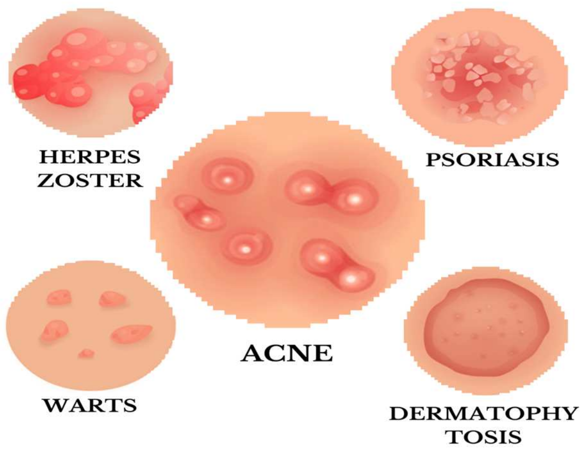

Fig. 1 Types of skin diseases

For the identification of various skin diseases using images and patterns, numerous advancements have been made by various researchers. One of the areas where machine learning can be used as the rapid and precise identification method for numerous skin disorders. Diseases may be categorized by image classification using machine learning models [6]. In the proposed work, a machine learning based deep learning model has been used for skin disease classification [7][8]. This model categorizes two classes namely; malignant and benign. These two classes correspond to two conditions having a high bad impact on health and the disease which can be cured easily [9]. The classification algorithms can be used for classifying different types of skin diseases such as acne, lichen planus, and sjs [6].

The proposed work has been divided into different sections. Section II incorporates existing work related to skin disease classification. Section 3 introduces the proposed methodology for skin disease prediction. Further, sections 4 and section 5 discuss the results and conclusion of the proposed research.

II. LITERATURE REVIEW

The work presented in [3] describes an extensive plan for the identification of skin-related diseases, which consists of three primary steps: data collection and preliminary processing, obtaining features by processing pictures, and categorization via machine learning techniques. For training and testing, they make use of a carefully selected dataset of pictures of skin conditions. The authors then used machine learning classifiers to precisely categorize skin disorders based on the retrieved data. The weakness of this researcher has been identified that the comparison with current techniques has not been done. Dataset with limited information, interpretability of models, and real-world obstacles etc. The authors have done an in-depth analysis of deep learning models' critical function in correctly detecting skin problems is provided in the review, which also emphasizes how these models have the potential to transform dermatology and enhance patient care. The authors deftly move from the generalities of skin disease image recognition to the particular, outlining the difficulties encountered in this field. The paper discusses well-known deep learning models and explores state-of-the-art methods including self-supervised learning, domain adaptability, and attention mechanisms, demonstrating their potential to improve skin disease image recognition even further. In [1], the authors utilized an RGB-based adaptive colour metric using a deep learning model for tumour detection. It aids in separating the tumour from the surrounding tissue. An appropriate coordinate transformation is used for image segmentation. By removing the tumour area from the segmented image, borders can be drawn. This technique worked well for diagnosing cancers, demyanov, and others. [5] The approach had excellent sensitivity and specificity for the identification of psoriasis vulgaris. Sumithra et al. presented a novel method for automatically segmenting and classifying skin lesions. In [2], authors combined the aforementioned methods with Markov random field (MRF) to categorize smooth pixels using two-dimensional digitized image division and scaling. The establishment of a trustworthy segmentation method has been further used. Salimi et al. [6] described an original skin identification algorithm that improves the recognition of skin pixels using colour models for RGB, HSV, and YCbCr. Deepa and Kotian in [10] studied the autodiagnosis method for skin disease classification. Techniques like image boundary detection and article mining are applied using MATLAB software. Kumar and Singh in [11] have used a different iterative stochastic region-merging method was suggested to separate skin lesion regions from the macroscopic images. Stochastic region merging was first carried out in this method at the pixel level, then at the region level until convergence. In [12] effortless skin lesion diagnosis was conducted. For the diagnosis, an algorithm is suggested in which training performance was monitored, and MAP estimation was done. In [13], an iterative stochastic region-merging approach was proposed to delineate skin lesion patches from the macroscopic pictures. In this technique, stochastic region merging is first done at the pixel level, then at the whole area level till convergence. In [14], the authors recommended an automated facial disease detection method using a CNN-based pre-trained model. This model uses pre-processing of the images, data augmentation of the dataset and achieved an accuracy of 88% in identifying eight facial skin diseases, including normal skin and no-face [15]. A CNN-based VGG16 model has been used to diagnose skin diseases like Actinic Keratoses, Basal Cell Carcinoma, Benign Keratosis, Dermatofibroma, Melanoma, Melanocytic Nevi, and Vascular Lesions. Results show that the CNN achieves 71.3%-75.2% accuracy, VGG16 achieves 80.3%, DenseNet 82.32%, Inception 80.45%, and an ensemble of VGG16, DenseNet, and Inception 83%-85% accuracy [16].
In [17], authors discussed deep learning-based models for detecting skin diseases. A transfer learning model, using VGG-16 based on the CNN technique has been used and compared with support vector machine, decision tree, linear discriminate examination, and KNN algorithm for linear classification. The highest accuracy of 98.7% was achieved using the VGG 16 CNN model with the KNN algorithm.

III. MATERIAL AND METHODS

Deep learning has been identified as a potential in several medical specialities, including dermatology, where it can help in early identifying skin diseases. The proposed work has been implemented using a CNN-based pre-trained VGG16 model. The dataset and proposed methodology has been introduced below

A. Dataset

To ensure the model's robustness and generalization, the VGG16 has been effectively trained on the skin disease dataset which contais a total of 44,000 images of two classes namely benign cases and malignant cases. There are various types of skin disease in the dataset namely, atypical melanocytic proliferation, cafe-au-lait macule, lentigo NOS, lichenoid keratosis, melanoma, nevus, solar lentigo, etc.

B. Methodology

The proposed work has been implemented with the CNN-based pre-trained VGG16 model. The work has several steps including, data pre-processing, model selection, hyperparameter settings, training the model and performance evaluation. Fig. 2 shows the proposed methodology for skin disease classification. The all steps have been described below:

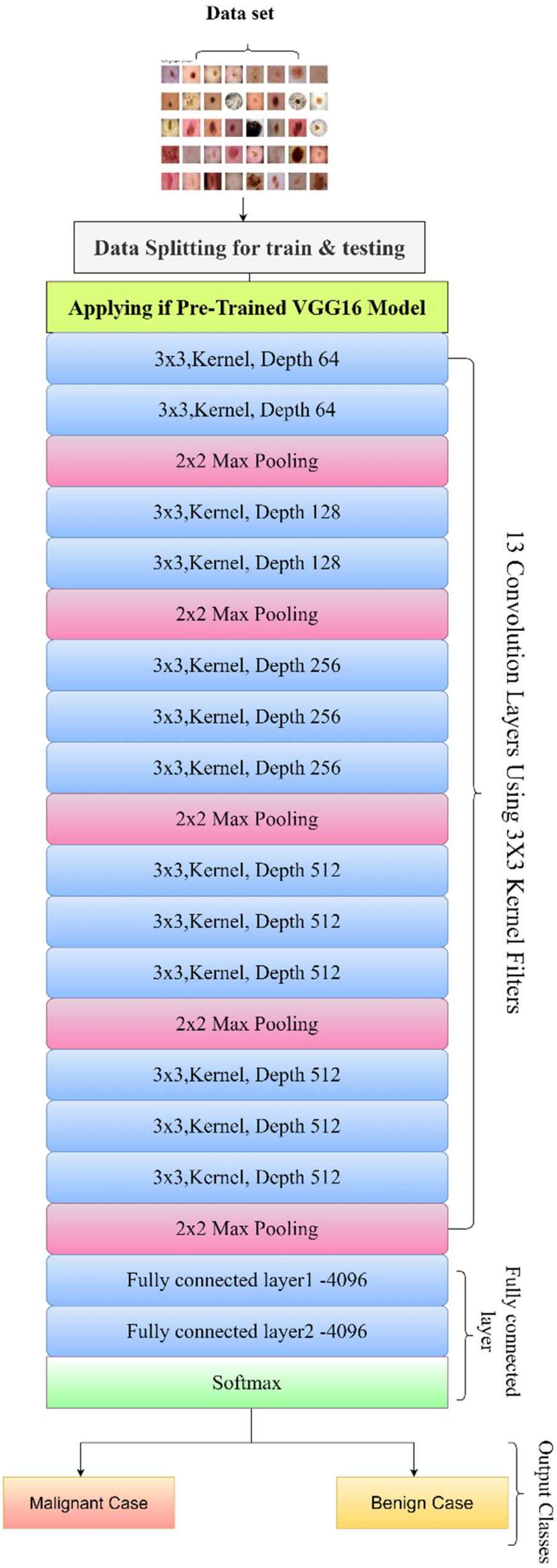

Fig. 2 Proposed methodology for skin disease classification

- Data processing: The images in the skin disease dataset have been scaled to a uniform size of 224X224. These pixel values are uniform.
- Model selection: In the second step, the selection of the suitable model for the skin disease dataset has been done. The literature review has been done for identifying the appropriate model. Various models namely,

convolutional neural networks (CNN), VGG, ResNet, Inception, and DenseNet have been found as promising models for achieving higher performance outcomes. However, VGG16 has been identified as the outperforming model for skin disease classification. Hence, it has been used in the proposed work for the classification.

- Transfer Learning: The proposed work has been implemented with a VGG16 model which is a transfer learning model containing 16 deep layers for the classification [18].
- Training: After applying the transfer learning, the dataset training has been performed and data is divided into two parts: training (70%), and testing (30%). The algorithm for deep learning is trained using training data and its performance is evaluated using test data after adjusting the hyperparameters and architecture as needed.
- Hyperparameter: To enhance model performance, fine-tuning of the hyperparameters has been done including acquisition rate change, epochs, batch size, and optimisation settings.
- Performance Evaluation: To evaluate the model's effectiveness in identifying various skin diseases classification. The test dataset was evaluated using metrics like accuracy, precision, recall, and F1-score, confusion matrix [19].
- Explain ability: For identifying the model's classification capability, the model's performance has been compared with the existing models.

CNN is a classification model which is used in various domains including agriculture, healthcare etc [20][21]. It is one of many artificial neural network models that are used for predicting classification outcomes from data sources [19].

A CNN is a network based on deep learning design that is frequently used for applications that process pixel input and recognize images. While CNN is the suggested network design for object identification and detection in deep learning, other types of neural systems can also be used[4]. They are therefore ideal for positions requiring computer vision skills and object recognition tasks, such as those used in self-driving automobiles

VGG16(Visual Geometry Group – 16 Layers): This deep learning model is a pre-trained CNN model that works in image recognition and classification tasks.

VGG16 is similar to a unique form of a computer program that can examine images and identifies what's inside the images. It excels in recognizing various items such as cats, dogs, cars, and others. In an image, the VGG16 can figure out what it contains. The program begins by inspecting the image in small sections, almost as if it were zooming in on distinct locations. It understands the colours and patterns in those tiny areas by using small coloured filters (similar to sunglasses). These filters assist the program in determining whether a given form or colour is important in detecting what's in the image. The algorithm combines all the information from the tiny bits and begins to understand what's happening in the big picture. The tool repeats this procedure several times with different filters and layers to improve its recognition of the things in the image.

Here's a breakdown of the components of VGG16:

Inputs layer: The model is given an image with three colour channels (red, green, and blue), typically 224x224 pixels in size. This image is then sent to the network to be processed.

Convolutional layers: VGG16 model is made up of 13 convolutional layers. These layers scan the input image and generate a map of features using tiny filters (typically 3x3 in size). Each layer searches for distinct patterns such as edges, corners, and textures. VGG16 can learn complicated and abstract information from photos by stacking these layers together. The Rectified Linear Unit (ReLu) activation function is utilized after each convolutional layer. It gives the network non-linearity, letting it learn more complex correlations between the input and the retrieved features. VGG16 employs max-pooling layers after a few convolutional layers. Pooling reduces the spatial dimensions of the feature maps while retaining the most relevant information. It aids in decreasing model computational complexity and preventing overfitting. VGG16's last section is made up of three fully connected layers. These layers use the high-level information learned from the convolutional layers to anticipate what objects or patterns are present in the input image. The final component of VGG16 is made up of three fully connected layers. These layers anticipate what objects or patterns are present in the input image using the high-level information learned from the convolutional layers. VGG16 frequently gets trained to decrease prediction mistakes by feeding it a large dataset of labelled images (e.g., ImageNet) and modifying its parameters (weights and biases) throughout the training process. Following training, the model can be utilized for picture categorization, object detection, and other tasks.

IV. RESULTS AND DISCUSSION

This section discusses the results of the proposed VGG16 model. The dataset is trained with the help of the CNN-based VGG16 model after training the model the outcome is predicted in loss and accuracy values.

A. Performance outcome of the proposed fine-tuned VGG16 model

This section depicts the performance results of the proposed model while keeping the epoch values as 10, 30, and 100.

Fig. 3 shows, at epoch value 30 and the batch size is 8, the model gives a validation_accuracy of min 72% and a maximum as 76%. The value of accuracy at training time is min 66% and max 75%. The loss value at validation is min 0.557 and maximum as 0.661 whereas the loss at training time is min 0.042 and max 0.046.

Fig. 4 shows that at an epoch value is 10 and the batch size is 8, the model gives an accuracy of 70.7&-79.3% at testing whereas for testing it has been achieved as 62%-79%. The loss value for the validation set has been identified as min 0.025 and max 0.059 whereas the loss value at training is identified as min 0.040 and max 0.049.

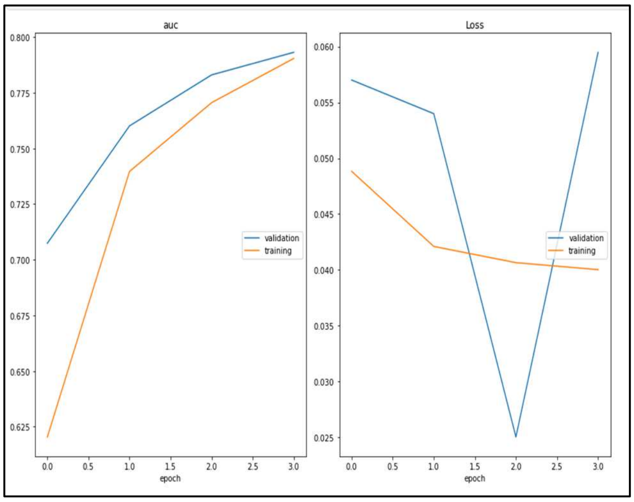

Fig. 3 Accuracy and loss of the proposed model with epoch value 30

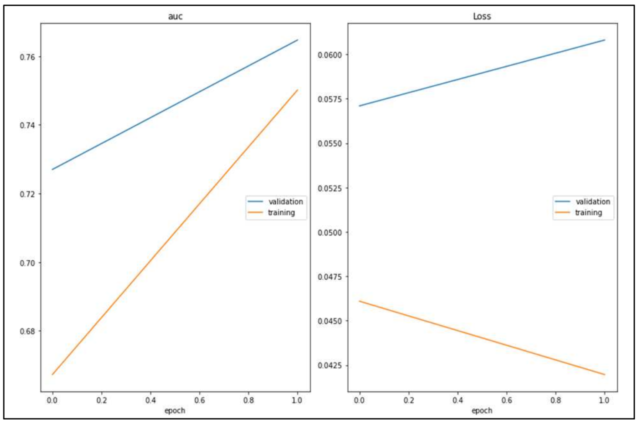

Fig. 4 Accuracy and loss of the proposed model with epoch value 10

Fig. 5 shows the confusion matrix of the proposed VGG16 model for skin disease classification (Class0 depicts the benign case, whereas Class1 represents the malignant case). Fig. 6 depicts the performance outcomes of the proposed VGG16 skin disease detection model.

Training Set			
TARGET / OUTPUT	Class0	Class1	SUM
Class0	33144 45.72%	5082 7.01%	38226 86.71% 13.29%
Class1	2033 2.80%	32241 44.47%	34274 94.07% 5.93%
SUM	35177 94.22% 5.78%	37323 86.38% 13.62%	65385 / 72500 90.19% 9.81%

Fig. 5 Confusion matrix of the VGG16 skin disease classification model

Each performance measures are calculated with the formulae which have been mentioned below:

Accuracy: (TP+TN) / (TP+TN+FP+FN) (1)

Precision: TP / (TP+FP) (2)

Recall: TP / (TP+FN) (3)

F1-Score: 2* (Precision * Recall) / (Precision +Recall) (4)

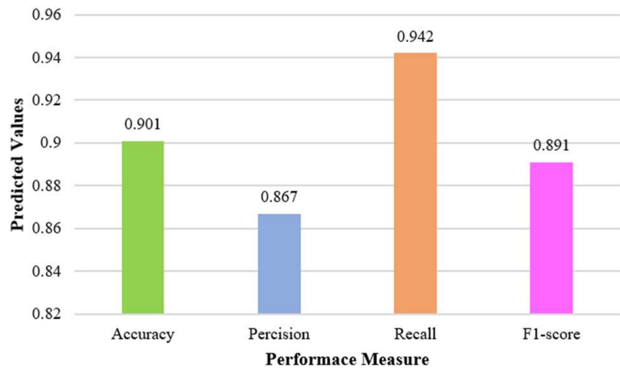

Fig. 6 Performance outcomes of the proposed model with epoch value 100

Fig, 6 shows the performance outcome of the proposed model with the epoch value kept as 100. The results have shown that the VGG16 model achieves 90.1% accuracy, whereas precision, recall, and F1-score have been identified as 0.867, 0.942, and 0.891, respectively.

B. Performance comparison of the proposed fine-tuned VGG16 model with the existing skin disease detection models

This section compares the accuracy of the proposed model with the existing models in terms of accuracy value.

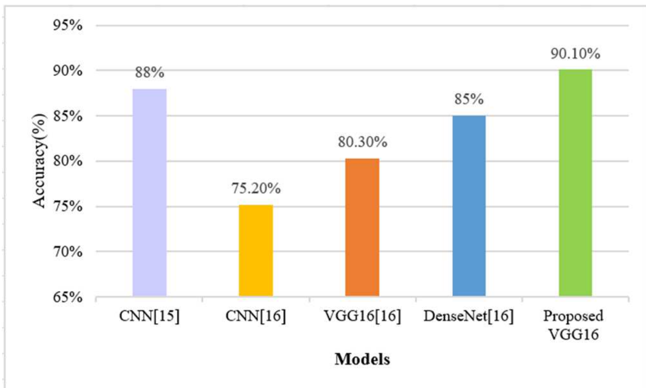

Fig. 7 Performance comparison of the proposed model with the existing models

Fig. 7 depicts the accuracy comparison of the proposed model with the existing models. This comparison identifies that the proposed model achieves the highest accuracy of 90.1% whereas other models have lower accuracy.

V. CONCLUSION

The integration of deep learning models with skin disease diagnostics holds significant promise in alleviating the strain on global healthcare systems. As the prevalence of skin issues rises and dermatologist availability remains limited in many regions, these novel algorithms have the potential to bridge gaps and offer more accessible and efficient medical services. This is especially beneficial for patients residing in remote or underserved areas, enabling early detection and treatment of skin ailments, thereby improving outcomes and enhancing their quality of life. By deploying a Convolutional Neural Network (CNN) model-based VGG16 architecture, a promising performance has been achieved in skin disease classification. The model's success is greatly influenced by both the quality and quantity of the training dataset, in addition to the meticulous tuning of hyperparameters. This approach involves the fine-tuning of a pre-trained VGG16, tailored to a specific skin disorder dataset, which proves advantageous, particularly when dealing with limited data. This research has aimed to leverage VGG16's proficiency in accurately identifying and categorizing various skin conditions from different images. Through rigorous training and fine-tuning, the VGG16 model's capacity to extract pertinent features and patterns from an extensive dataset of annotated skin images has been achieved. The proposed model has achieved an accuracy of 90.1%, an F1-score of 0.891, a recall of 0.942, and a precision of 0.867. The results have been compared with the existing models which shows that the proposed model outperforms the existing model's performance.

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