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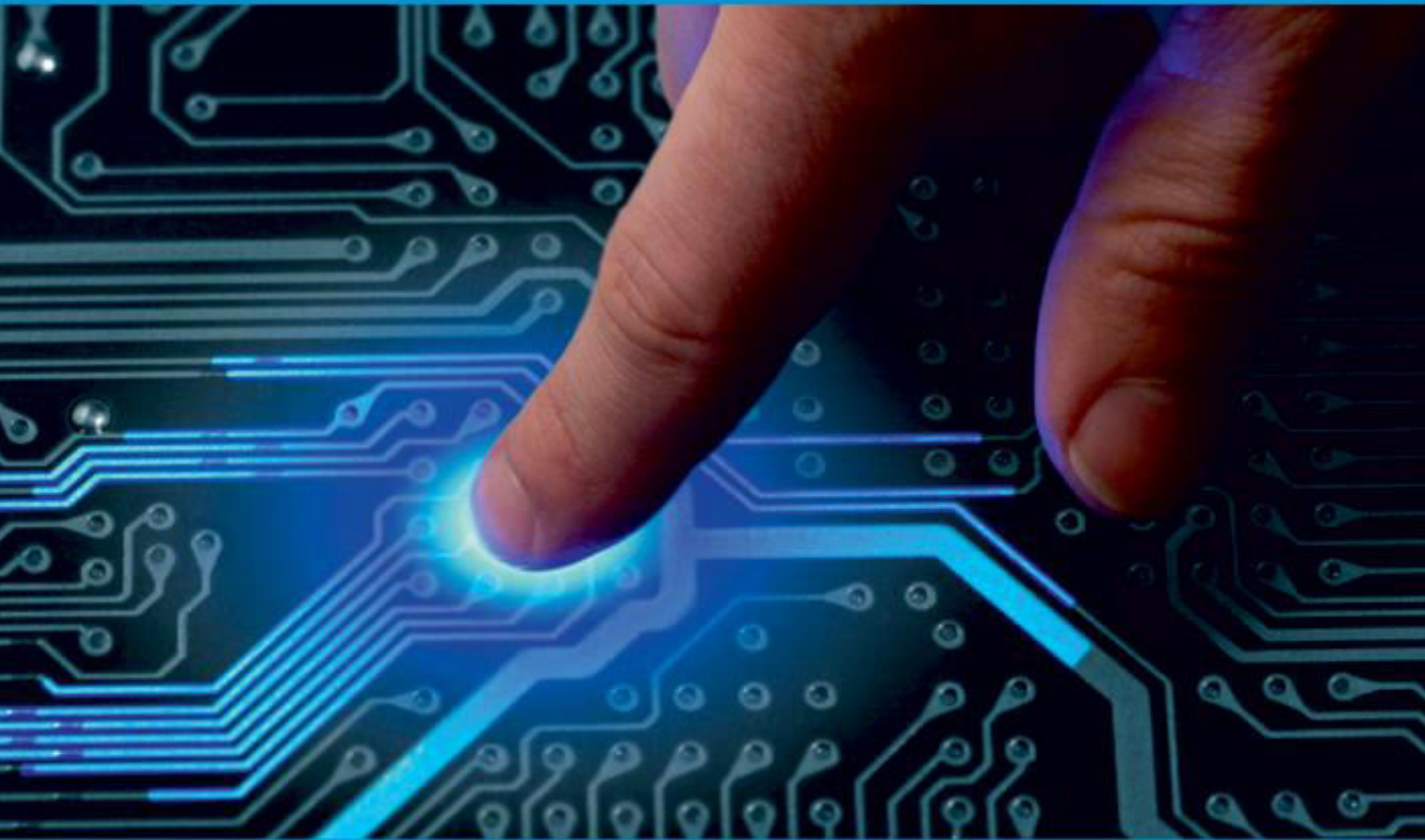
e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 11, Issue 7, July 2023

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107065 |

Development of Deep Learning Model for Varied Skin Disease Classification

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ABSTRACT - Skin Diseases pose a serious threat to global health since millions of people worldwide are affected by various skin conditions. Diagnosis of these skin diseases on time is necessary for effective treatment and to help improve patient medical health. This paper presents the development of a deep learning model for varied skin disease detection and classification. The varied skin diseases used to train the model for classification are Basal Cell Carcinoma, Benign Keratosis like Lesions, Eczema, Melanoma, Warts and Healthy Skin. The paper compares different deep learning models, to see how well they can identify and classify various skin diseases. Transfer learning technique is implemented on the skin disease dataset to leverage the learned features and optimize model training. The pre-trained convolutional neural network (CNN) models - VGG, ResNet, MobileNet and their variants are used and the results are then compared to find out the model that gives us more accurate predictions. The model's performance measure is evaluated using appropriate evaluation metrics to measure accuracy and precision. The model is then deployed to build a web application using Flask and progressive web applications for mobile devices. This serves as a valuable tool for users, dermatologists, and healthcare professionals in diagnosing skin diseases and taking the necessary steps for appropriate treatment and care.

KEYWORDS: Deep Learning, Convolutional Neural Network (CNN), VGG, ResNet, MobileNet, Evaluation metrics

I. INTRODUCTION

The human skin is not only the largest organ in our body but also a critical defence mechanism against external elements, playing a crucial role in safeguarding our overall health. Skin diseases can exert a profound impact on an individual's well-being, affecting not only physical health but also having psychological and social ramifications. Timely diagnosis of skin conditions is essential as it can lead to improved patient outcomes, lower healthcare expenses, and ease the strain on healthcare systems [1]. The objective of this project is to create an advanced deep learning model capable of accurately classifying different skin diseases. Since skin conditions can manifest in diverse ways, precise identification is crucial for appropriate diagnosis and treatment. Conventional diagnostic approaches heavily depend on dermatologists' expertise, which can be time-consuming and prone to errors. Through the implementation of deep learning techniques, the goal is to automate the classification process, offering patients a reliable and efficient tool for early diagnosis, as well as providing valuable support in dermatological diagnosis [2].

Deep learning, as a specialized branch of machine learning, empowers computers to autonomously learn and comprehend intricate patterns within vast datasets [3]. Its capability to process high-dimensional data and automatically extract relevant features has driven remarkable progress in diverse fields. Among the various types of deep learning models, Convolutional Neural Networks (CNNs) have emerged as a prominent and widely-used architecture, delivering state-of-the-art results in various domains [4]. In the context of skin disease recognition, deep learning algorithms are utilized to analyze skin images and effectively classify them into different disease categories. The system proposed for this task employs a variety of CNN models such as ResNet, MobileNet, VGG, and their variants, as well as pre-trained models, for the training and evaluation process [5]. To assess the performance of these trained models in skin disease classification, validation data is used for evaluation.

Convolutional Neural Networks (CNNs) are a class of deep learning models uniquely tailored for image processing tasks. By utilizing convolutional layers, these networks can automatically detect and extract intricate visual features from input images. CNNs have brought significant advancements in image classification, surpassing conventional methods with their exceptional accuracy. Their hierarchical learning capability enables them to excel in various tasks, including object recognition, facial recognition, and scene classification. After evaluating all the models, the most accurate and dependable one is selected for deployment. This chosen model is then integrated into a web application, offering users an interface to upload skin lesion images and obtain automated diagnosis and classification results. This accessible deployment ensures convenient and timely skin disease recognition for users. Additionally, a Progressive Web Application (PWA) [11] conversion is implemented, transforming the web application into a mobile application

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107065 |

for easy access on users' mobile devices. This advancement allows users to capture real-time skin images and receive instant disease diagnosis.

II. LITERATURE REVIEW

Computer vision-based methodologies are used to predict different types of skin diseases. The algorithms such as Support Vector Machine (SVM) Classifier, Free Timberlands, Repeated Neural Organizations and CNN's Organization computations can be used to perform tests. Recurrent Neural Network (RNN) architecture is one of the models that delivered best performance for skin disease detection among the compared methodologies [1]. The main objective is to develop a system that can diagnose skin diseases based on images of infected skin. The deep learning architectures like MobileNet V2, which is a variant of Convolutional Neural Networks (CNNs) can be used to build and train the model for this task [2].

Using Convolutional Neural Networks (CNNs) for the identification and diagnosis of melanoma, a type of skin cancer was performed in one of the research projects. The dataset used for training and evaluating the models was ISIC dataset that consists of 2637 images. The proposed model, implemented using keras python library, aimed to classify the skin cancer images into two categories, benign (non-cancerous) or malignant (indicating melanoma). The study compares two different models, among which one used the technique of transfer learning, employing the VGG16 architecture. The evaluation of the models demonstrated that the transfer learning approach with the VGG16 model achieved better accuracy compared to the other model. The reported accuracy of 88% suggests that the proposed model was successful in distinguishing between benign and malignant skin cancer cases [3].

One of the researchers performed the classification of the different skin disorders the colour and texture features were used. The entropy, variance, and maximum histogram value, are extracted from the Hue-Saturation-Value (HSV) colour space and used for classification. Machine learning models, specifically Support Vector Machine (SVM) and Decision Tree (DT), are employed to build the classification models using these colour and texture features to help the classifiers learn patterns and relationships between features and disease classes [4].

The classification of skin diseases using deep learning involves utilizing deep neural networks to analyze and classify the skin images based on their characteristics [5]. Different models such as ImageNet, GoogleNet, LeNet, VGG. TensorFlow, Caffe and Theano are the deep learning frameworks used for training the model.

The detection of skin diseases such as Actinic Keratosis and basal cell carcinoma, which have the potential to become malignant over time. The researchers employed two popular deep learning architectures, VGG16 and MobileNet for training the model. Both architectures have proven effective in various image classification tasks, including medical imaging. After training the models using a suitable dataset, the researchers achieved an accuracy of 80% for classifying skin lesions as either Actinic Keratosis or basal cell carcinoma. The trained models were then integrated into a system that can analyze the lesions and provide real-time predictions [6].

Convolutional Neural Network (CNN) is used to reduce the noise present in the database to improve the quality of the dataset by reducing noise and enhancing the features relevant to the classification. Algorithms are proposed for dividing a cutaneous lesion into cutaneous images relying on the utilization of the straight active-contour and morphological processes [7].

Support Vector Machine (SVM) and k-Nearest Neighbours (KNN) algorithms can also be employed to perform the classification of the cutaneous lesions. The diagnosis of skin cancer, specifically classifying melanoma from benign skin lesions can be done using the Convolutional Neural Network (CNN) algorithm [8]. For evaluating the performance and classification results of the trained model the faster Region-CNN was used. R-CNN is a technique for object detection and localization in images.

The machine learning algorithms like Support Vector Machines (SVM) and Random Forest methods used for skin disease detection. The traditional diagnosis methods of skin disease detection lack the medical resources and the accuracy of diagnosing is low. The study says that around 5.4 million new skin cancer cases are recorded every year, one out of five will be diagnosed with cutaneous malignancy, and around 10000 deaths in the US due to Melanoma [9].

Xception, Inception ResNet-V2, and NasNetLarge algorithms are also used for skin lesion classification. The training

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images used in one of the papers were provided by the ISIC2019 organizers. The paper also highlights the challenges of class imbalance and outliers in skin lesion classification [10].

To summarize, better accuracies were obtained using transfer learning techniques [3]. There is a shortage of research in this field, models must be developed and implemented to detect the disease at an early stage and take proper measures [5]. Architectures like VGG16 and MobileNet resulted with accuracy of 80% [6]. From the literature survey – most of the results show higher accuracy using the Deep Learning Algorithms such as CNN and its models like ResNet, VGG and their variants [2-9].

The traditional method lacks the medical resources and accuracy of diagnosis is low [9] and this can be resolved by automating the skin disease detection process. Skin disease detection based on Machine Learning requires a large amount of time and energy, whereas using Deep Learning the significant feature representations are automatically learned from the raw data [5-7].

III. SYSTEM DESIGN

The system design for the development of a deep learning model for varied skin disease classification is to automate the process of diagnosing the skin disease to help patients know their disease and take treatments to improve their medical health. The System Design shows the overall system design of Varied Skin Disease Classification. The dataset is gathered for varied skin diseases, most commonly caused skin diseases. The data split is then carried out on the data collected. We have split the data as 70% for training data, 15% each for testing data and validation data. The training data is the pre-processed where data resizing and augmentation is done, then this pre-processed data is used in the training process to train the model. Once we have our model trained, the model is evaluated to measure its performance and accuracy with the testing data in the testing process. Then based on the input image given to the model for testing, the classification results are obtained, in this paper the model classifies the results into 6 classes - Basal Cell Carcinoma, Benign Keratosis like Lesions, Melanoma, Eczema, Warts or Healthy skin.

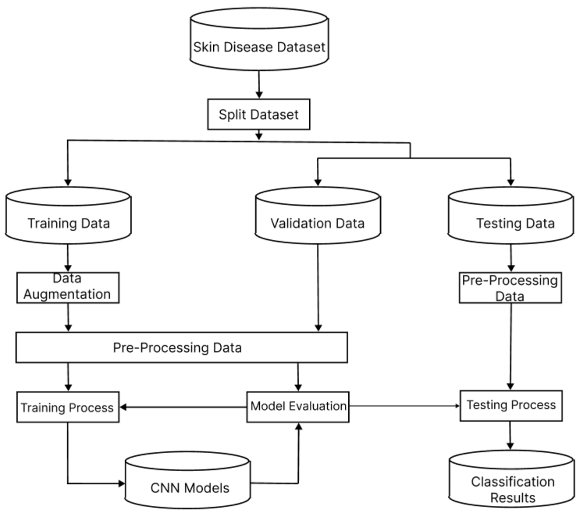

Fig. 1 System Design for Varied Skin Disease Classification

IV. TECHNOLOGIES

CNN

Convolutional Neural Networks (CNNs) are specialized deep learning algorithms designed specifically for image processing tasks. These networks consist of layers that utilize convolution and pooling techniques to extract essential information from images. Through training with labelled data and weight adjustments, CNNs aim to minimize prediction errors, making them excellent for tasks like image segmentation, object detection, and classification [12]. Several widely known CNN architectures, including LeNet, AlexNet, VGG, GoogLeNet, ResNet, DenseNet, MobileNet, and EfficientNet, have each demonstrated exceptional performance in various computer vision tasks. LeNet and AlexNet were early pioneers, while ResNet addressed the vanishing gradient problem with innovative residual

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connections. MobileNet was designed for optimal performance on portable devices, and VGG is well-regarded for its simplicity and effectiveness. These diverse CNN architectures have revolutionized the field of computer vision and continue to drive advancements in image processing and recognition tasks.

AlexNet

AlexNet, created by Alex Krizhevsky and his team, gained widespread recognition when it emerged victorious in the 2012 ImageNet Large-Scale Visual Recognition Challenge. This pioneering architecture comprises several convolutional layers, pooling layers, and fully connected layers, while incorporating the rectified linear unit (ReLU) activation function and dropout regularization, which played a key role in its exceptional performance. The triumph of AlexNet in the ImageNet challenge marked a significant milestone in the field of computer vision, inspiring further advancements in deep learning and convolutional neural networks. Its innovative techniques and impressive accuracy have influenced subsequent CNN architectures and their applications in various domains.

ResNet

ResNet is an exemplary architecture for deep neural networks, incorporating skip connections, also known as residual connections, to overcome the challenge of vanishing gradients that occurs with increasing network depth. Variants like ResNet-50, ResNet-101, and ResNet-152 have different architectures, denoting the total number of network layers, including convolutional, pooling, and fully connected layers. The fundamental building block of ResNet is the residual block, enabling the integration of skip connections during the training of extremely deep networks [13]. ResNet's innovative approach to skip connections revolutionized deep learning, allowing for the successful training of much deeper networks and contributing to state-of-the-art performance in various computer vision tasks. Its versatility and adaptability have made it a widely adopted and influential architecture in the field of convolutional neural networks.

MobileNet

MobileNet is specifically engineered to deliver efficient inference on embedded and mobile devices [14]. It comprises various variants, including MobileNetV1, MobileNetV2, and MobileNetV3, each offering a distinct architecture tailored for specific needs. The number of layers in each version varies, with MobileNetV1 and V2 having 23 and 53 layers, respectively. In contrast, MobileNetV3 introduces large and small variants with 213 and 53 layers, respectively, encompassing various types of layers such as pooling layers and convolutional layers. MobileNet's versatility and performance have made it an indispensable tool for on-device inference, enabling real-time and power-efficient applications on resource-constrained platforms. The ongoing development and refinement of its variants continue to drive advancements in mobile deep learning and edge computing.

VGGNet

The Visual Geometry Group (VGG) architecture stands out for its depth and larger parameter count, resulting in potential computational challenges during training and inference compared to some other architectures. VGG16 and VGG19 are two well-known variations of this architecture. VGG's distinct characteristic is its heavy utilization of 3x3 convolutional filters, which are applied repeatedly throughout the network. The name of each variant indicates the total number of layers, encompassing both convolutional and fully connected layers. Despite the computational demands, VGG's depth and unique filter approach have contributed to its effectiveness in various computer vision tasks, making it a widely studied and influential architecture in the field of deep learning [15].

In this research, we'll implement a custom CNN model and also implement pre-trained VGG, ResNet, and MobileNet architectures through transfer learning. After comparing the best model, we'll deploy it into a practical application for real-world usage.

V. IMPLEMENTATION

Dataset:

The dataset utilized in the research paper consists of a collection of images of various skin diseases. It includes a diverse range of skin conditions commonly encountered in the clinical practices. It includes varied skin diseases like Basal Cell Carcinoma, Benign Keratosis like Lesions, Eczema, Warts and Melanoma. The dataset comprises images from patients with different demographic characteristics, skin types depicting various skin conditions affecting different parts of the body such as face, arms, legs, fingers and other relevant areas. In addition to the various skin conditions, the dataset also consists of images of healthy skin that were captured using a mobile camera and serve as representative samples of normal skin condition. Including the normal skin in the dataset helps the model to learn and

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distinguish between healthy and diseased skin, enhancing the ability to accurately classify the varied skin conditions. The collection consists of around 6000 images in total belonging to different skin conditions.

Fig. 2 Samples of skin diseases from the training set

Dataset Collection and Preparation:
To gather and organize the dataset for skin disease images for development and evaluation of deep learning models. The data collection involves gathering the raw images of varied skin conditions captured from different body parts, and covering a wide range of demographics. The data is then divided into training, validation and test split to enhance the evaluation and optimize the performance of the model. As a result, we get an organized dataset of varied skin diseases, training set, validation set and test set.

Data Pre-processing:
This step is carried out to pre-process the skin images before feeding them into a deep learning model for training. Image resizing is carried out to resize the images to a consistent resolution that is suitable for input to the deep learning model and ensure that all images have the same dimensions to maintain consistency during training and inference. As a result, we obtain pre-processed images that are resized to suitable form for feeding into deep learning model for training.

Model Training:
To define the structure and organization of the deep learning model used for skin disease classification, optimize the model's parameters to minimize the training loss and improve its ability to accurately classify skin diseases. Model training involves defining the convolutional layer, pooling layers, activation function, fully connected layers of the selected architecture and parameter optimization, loss calculation, training loop - training the dataset for multiple epochs. As a result, we get a trained deep learning model for skin disease classification.

Model Evaluation:
To assess the performance and effectiveness of the trained deep learning model for skin disease classification, then evaluate the model's prediction for a test set to measure the accuracy. The predictions, performance metrics calculation, visualization, fine-tuning and re-training of the model are carried out.

Model Deployment and Integration into Web Application:
To deploy the trained deep learning model to build a web application using flask framework for making it accessible to the users for diagnosing. A web application is built using the flask framework to implement user interface components for image upload and generate results.

The Fig. 3 is the architecture diagram for the system where it shows the overall outline of the application.

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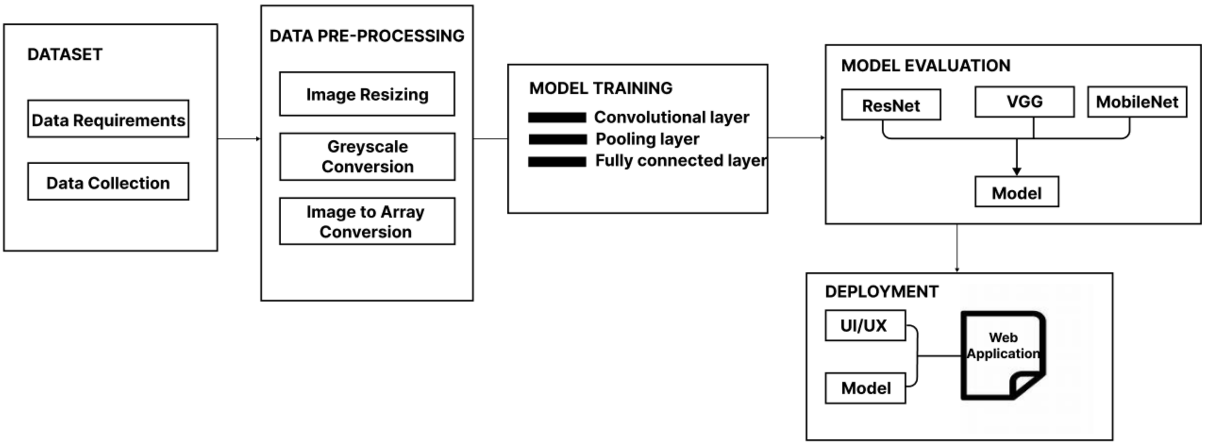

Fig. 3 Architecture Diagram for Varied Skin Disease Classification

VI. RESULTS

The deep learning model, trained on a diverse dataset of skin disease images, exhibited remarkable accuracy in distinguishing between various skin conditions. Among the tested CNN architectures, MobileNet demonstrated the highest accuracy of 83%, leading to its deployment in the application. A web-application was developed using the Flask framework. Using Progressive Web Application (PWA), the web- application was then transformed to mobile application, to help the users to access the application from their mobiles. The user-friendly interface of the application enables users to upload skin images, which are then processed using the MobileNet-based classification model, providing real-time diagnosis results for efficient and effective skin disease classification.

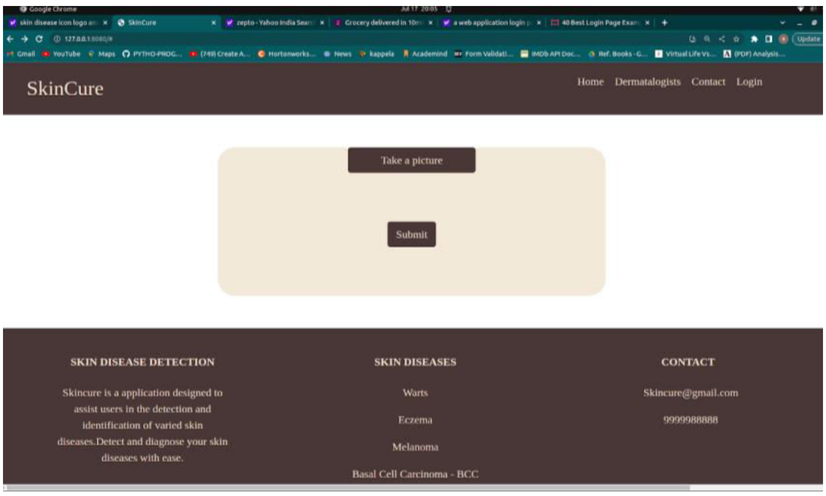

Fig. 4 Home Page of the Skin Disease Classification Web Application

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|| Volume 11, Issue 7, July 2023 ||
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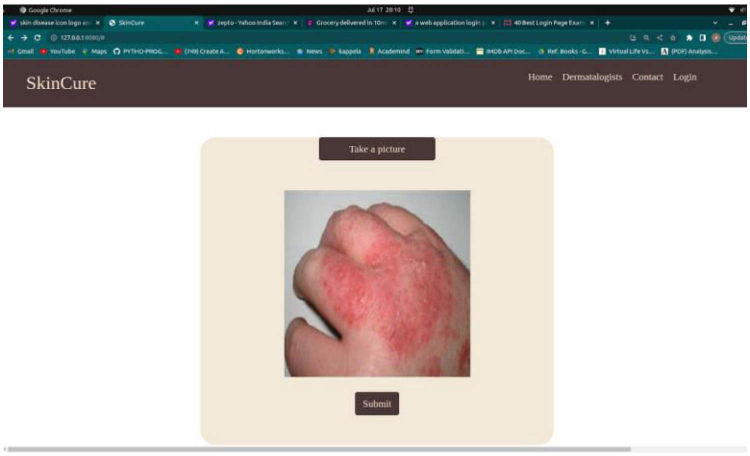

Fig. 5 User can upload the skin image clicking “Take a Picture” and give Submit

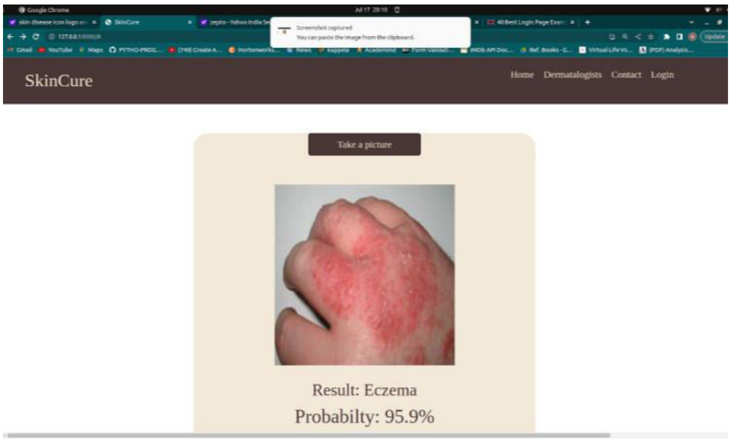

Fig. 6 The results are displayed showing the skin image has “Eczema” with confidence score of 95.9%

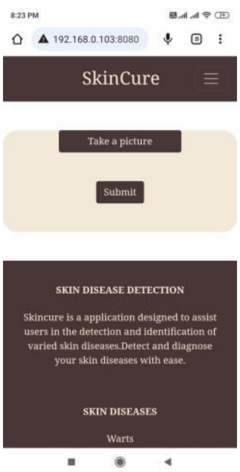

Fig. 7 Home Page of the Skin Disease Classification on Mobile Device

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

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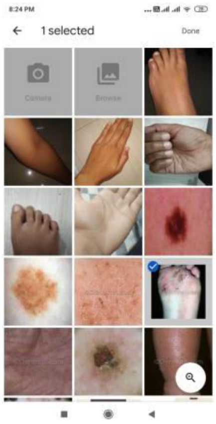

Fig. 8 The user can upload the skin image from the mobile device or capture real-time image using the camera

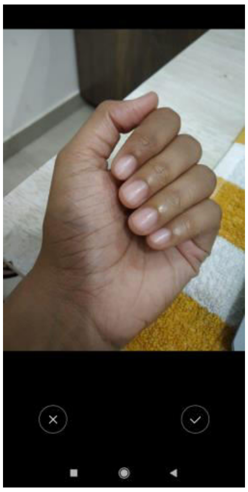

Fig. 9 The user can capture real-time image using the camera

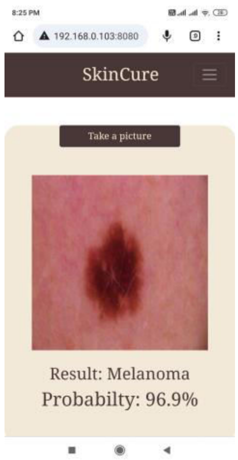

Fig. 10 The results displayed as “Melanoma” on mobile device

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

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VII. CONCLUSION

The dataset (70%) is trained using the CNN algorithm and its architectures to obtain the desired results. The system allows the users to upload the skin images from their system and analyze the results. The system takes the uploaded image and detects the type of skin disease - Basal Cell Carcinoma, Benign Keratosis like Lesions, Melanoma, Eczema, Warts. If the skin image provided by users doesn't contain any skin lesions, then it will be displayed as healthy skin. The system can detect the skin disease and serves as an efficient tool for the patients to help in early diagnosis and improve their medical health.

The research paper demonstrates that deep learning models, specifically the ResNet, VGG, and MobileNet architectures, are effective in detecting and classifying varied skin diseases. These models can accurately identify different types of diseases based on their unique features. ResNet performs well with its deep architecture and unique connections, while MobileNet is particularly efficient in terms of computational requirements. Both architectures offer promising solutions for automated skin disease detection.

The findings of this study contribute to the development of automated systems that can help patients identify and manage skin diseases more effectively. By utilizing deep learning models, users can take timely actions to prevent crop damage and enhance overall productivity. Further research can focus on exploring new architectures and techniques to improve the accuracy, efficiency, and interpretability of skin disease detection models. Additionally, investigating the applicability of these models across different disease types would be beneficial.

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