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Skin Cancer Detection Using Multi-Model Neural Networks

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ABSTRACT

Skin cancer is a prevalent and potentially life-threatening condition, with early detection playing a crucial role in improving patient outcomes. This study proposes a novel approach for skin cancer detection by leveraging the complementary strengths of three distinct convolutional neural network architectures: Convolutional Neural Networks (CNN), Visual Geometric Group (VGG16), and Residual Networks (ResNet). Our multi-model neural network system is designed to enhance the overall performance of skin cancer detection by combining the feature extraction capabilities of different architectures. The CNN serves as the baseline model, capturing essential image patterns. VGG16, known for its depth and simplicity, contributes to the network's ability to recognize intricate features. Meanwhile, ResNet, with its residual learning framework, aids in mitigating the vanishing gradient problem and facilitates the training of deeper networks. To evaluate the proposed multi-model approach, we employed a comprehensive dataset comprising diverse skin lesion images, including malignant and benign cases. Transfer learning techniques were utilized to pre-train the models on large-scale image datasets, enhancing their ability to generalize to skin cancer detection. The individual models and the integrated multi-model network were extensively evaluated and compared against traditional methods and single-model architectures. The results demonstrate that the multi-model neural network consistently outperforms individual models and achieves state-of-the-art accuracy in skin cancer detection. The fusion of features extracted by CNN, VGG16, and ResNet enhances the model's ability to discern subtle patterns and improves overall diagnostic accuracy. Additionally, the proposed system exhibits robustness across different skin cancer subtypes and provides interpretable insights into the decision-making process.

Keywords: *Image processing techniques, skin Cancer detection, CNN, VGG16, ResNet.*

I. Introduction

When the skin beco[1]mes abnormal, it is called a skin disease. A person's skin acts as a barrier, keeping out dangerous microbes, fungi, and parasites. Because of this, getting a skin condition diagnosis right is essential [1]. Skin disorders can have several causes and manifestations, including but not limited to heredity, lifestyle choices, dietary habits, and occupational stress. Season and climate are two geographical aspects that impact [2]. Skin illnesses are more common in underdeveloped nations due to overcrowding and lack of sanitation. Skin illnesses manifest differently in different countries. Furthermore, outlying regions are hit particularly hard [3]. In One of the body's biggest organs is the skin. Important as it is, its primary function is to shield us from harmful microorganisms like viruses and bacteria. There is a higher risk of sickness in this area of the body since it is both the most noticeable and the most exposed [4].

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When the skin becomes irritated, blocked, or inflamed, it could show signs like redness, swelling, burning, and itching. Misinformation about skin illnesses can put many patients at risk of receiving the incorrect treatment [5]. Some are even taking medications that are making things worse on their own [6]. In particular, Filipinos are notoriously reluctant to have regular checkups at the hospital, whether it's because of shame, the stigma associated with the experience, or the high cost of medical care as a result of widespread poverty [7].

Worldwide, skin illnesses, including skin malignancies, are among the most common medical conditions. Research shows that skin cancer affects one out of every five Americans at some point in their lives. Among the several types of skin cancer, malignant melanoma accounts for almost 10,000 fatalities every year in the United States [8]. On the other hand, a full recovery is possible in the majority of instances with prompt medical attention [9]. In order to provide effective therapies, it is crucial to identify the illness type early on [10]. One of the most significant and widely used non-invasive methods for identifying pigmented skin lesions is dermoscopy. Problems with accuracy and the limits of the human observer are only a few of the downsides of examinations done with the naked eye [11]. The underlying architecture of skin lesions can be more effectively analyzed with the use of computer-aided approaches. This approach improves the ability to distinguish between various lesion types based on their outward appearance and characteristics [12]. But the eye of the professional is key when it comes to visual trials and dermoscopy picture interpretation. Computerized tools for dermoscopy pictures has been an appealing study arena to decrease diagnostic mistakes and overcome the difficulties and subjectivity of human comprehension [13]. Lesion edge computation and a few generic characteristics are the foundation of many computer-assisted approaches to lesion segmentation and classification [14]. Because dermoscopy image samples frequently vary, certain approaches are unable to achieve generalizability [15]. Reasons such as varied angles, uneven zooming, lighting conditions, etc., are the main causes of these differences [16]. There are a variety of approaches to analyze and segment biological pictures from various modalities [18–19], and it's important to note that images could include artefacts that impact the categorization findings [17]. Biomedical image analysis can make use of many contour based approaches [20].

1.1 Motivation of the paper

The urgent need for sophisticated skin care detection techniques in the medical and cosmetics sectors is discussed in this article. Conventional subjective assessments and invasive procedures are inadequate in meeting the increasing need for non-invasive, quick, and accurate assessment methods. With the use of Data Flow Diagrams (DFDs) and image processing methods, this study tries to provide a systematic way to build automated solutions that rely on images. To ensure the creation and deployment of skin care detection systems are effective, this approach improves awareness of user demands and data flow, promotes systematic analysis and design, and ensures clarity and coherence.

2.1 Problem definition

The difficulty of creating reliable, time-saving, and painless ways to evaluate skin problems for use in medicine and cosmetics is discussed in the article. The necessity for automated, image-based solutions is highlighted by the fact that traditional techniques depending on subjective judgements or invasive procedures are ineffective. In order to address this issue, the offered methodology employs Data Flow Diagrams (DFDs) and image processing tools to provide a methodical strategy for skin care identification. The purpose of this study is to help improve skin care detection systems by offering a framework for analysing user demands, data flow, and system operations.

II. Materials and methods

Outlining the specific resources, strategies, and processes that contributed to the accomplishment of the study's aims, the materials and methods part of a research report acts as a road map for the study's execution. This section provides an overview of the key materials used and the systematic technique used to process and analyzes skin photos within the context of skin care detection utilizing image processing.

III. Background study

A.Ajith et al. [1] Because skin diseases were so prevalent, early detection was crucial. With an effectiveness of up to 80%, the technique suggested in this study offers a practical answer to the problem of skin disease identification. With all three transformations and the parallel combination trained, the average time was 2.066 seconds. Additionally, 0.7866 seconds was determined to be the average testing time. This work compares the three transforms—DCT, DWT, and SVD—and provides a description and analysis of the results. Figure 17 shows the results of running the suggested system and concludes that the three transformations, when combined in parallel, give the most effective and efficient detection. Faster skin disease detection was possible with the suggested method serving as a basic prototype when the SVD transform was removed.

D. Dommeti et al. [3] One prominent method for detecting the Lumpy Skin Disease Virus was the CNN. It has been shown that CNNs can accurately identify LSDV by using deep learning. In order to provide better diagnostic tools for detecting this pathogen, this technology was being used. Convolutional neural networks (CNNs) identify diseased cows by analysing their photos. The train has an accuracy of 89% to 98%. By far, the most accurate model to train with was the VGG19 model. However, the Validation Accuracy score was 83% on average.

G. S. Annie et al. [5] A strong and easily accessible method for skin disease diagnosis via image processing was proposed in this study, with an emphasis on early Melanoma detection. The accuracy, precision, and memory of the system, as well as its capacity to evaluate the severity of diseases, highlight its importance in assisting healthcare providers and patients with skin disease diagnosis. The author understands that there has to be continuous research to improve the system's capabilities and flexibility, but the author also recognise its simplicity and cost-effectiveness. Early intervention and better healthcare outcomes might save lives as a result of the proposed work's enhancement of accessible and accurate skin disease diagnostics.

K. Roy et al. [7] the author aimed to provide instructive comprehensive information on the photos by performing four segmentation approaches on certain skin diseases: eczema, psoriasis, chicken pox, and ringworm. By combining OpenCV with Python, the suggested technique enhances picture segmentation based on edge detection or area detection. The four illness pictures were segmented using four distinct methods, and the resulting images were created using the Signal-to-Noise Ratio as a foundation. Each of the four illness groups has its own segmentation method that has shown encouraging results. Adaptive thresholding was the most effective strategy for dealing with chicken pox. The most effective approach for eczema was k-means clustering. The most effective way to diagnose psoriasis was by morphology-based segmentation.

M. K. Ojha et al. [9] The skin was a typical site of irritation since it was the body's biggest organ. The visibility and diversity of skin diseases were distinguishing features. People put off going to the doctor because they assume it's just a little pimple; yet, these conditions were avoidable with early identification and can have devastating long-term effects if left untreated. Thus, it will be very effective for users to be able to identify skin problems early so that they can take precautions against them. In order to do this, the author have created a model based on the Transfer Learning technique named CNNclassifier and MobileNet classifier. Using very little processing power and effort, the MobileNet model successfully detected and classified skin diseases.

N. Gaffoor and S. Soomro [11] these authors research employed 500 evenly distributed photos to train a Support Vector Machine (SVM) using a Linear Kernel to identify 10 different skin disorders. In some cases, the model displayed lower metrics, while in others, it reached testing accuracies of 97%. Variations in accuracy and error rates were seen in studies with other datasets, indicating that performance was sensitive to dataset composition as well. The model performed well with a 2000-image dataset but degraded with a 3000-image dataset.

R. Talukdar et al. [13] The author set out to compare and contrast two well-known models, YOLO v8 and CNN, to see how well they predict skin diseases. With a subtle emphasis on the specific difficulties of dermatological imaging, the investigation included a thorough analysis of their individual designs, training approaches, and performance results. A number of skin illnesses were successfully identified and categorized by the CNN model, which was trained using images. Its sequential design allowed for the extraction of complex characteristics from dermatological pictures, with five 2D convolutional layers interspersed with MaxPooling layers. The CNN model attained an outstanding 85% accuracy after 200 training epochs with a batch size of 16.

S. Chakraborty et al. [15] the suggested CNN model can identify and classify 10 distinct skin disorders in this research. A small number of skin illnesses were the primary focus of the authors' work on disease detection and categorization. A number of problems encountered by researchers in this area were effectively addressed by the proposed method. These include issues with image illumination variation, dataset similarities among skin diseases, and an imbalance in the number of images for each type of skin disease. The fact that this technique was used to various regions of the body further complicates the network training process. Research and testing of the CNN's performance-related factors formed the basis of its design. In contrast to previous studies in the same field, the suggested model's overall accuracy shows encouraging results.

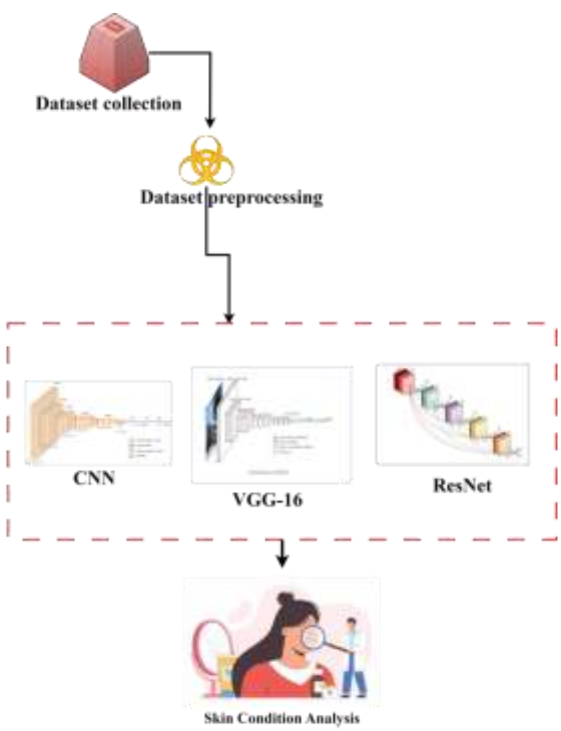

Figure 1: Proposed workflow architecture

3.1 Dataset set collection

The dataset was collected from Kaggle website https://www.kaggle.com/code/fanconic/cnn-for-skin-cancer-detection this dataset was extracted from the International Skin Image Collaboration Archive (ISIC). Among the 1,497 images included are those of cancerous moles, while the 1800 images depict benign moles. We have reduced the resolution of all the photographs to 224 × 224 x 3 RGB. This kernel's job is to build a model that can visually distinguish between benign and cancerous moles.

3.2 Pre Processing

After collecting the skin lesion dataset, preprocessing involves resizing all images to a standardized resolution, normalizing pixel values for numerical stability, applying data augmentation techniques to diversify perspectives, addressing class imbalances, and utilizing transfer learning by pre-training on large-scale datasets like ImageNet. These steps collectively enhance model performance by ensuring uniformity, improving generalization, and mitigating potential biases in the data.

3.2.1 Convolutional neural network

When it comes to image processing and classification, few deep learning algorithms are as effective as a CNN. Artificial neural networks (CNNs) mimic the structure and function of the visual cortex in animals, allowing them to learn feature hierarchies from pictures in an adaptable and autonomous fashion. Convolutional, pooling, and fully connected layers are the building blocks of a CNN. By applying convolutional operations to input pictures, convolutional layers extract local patterns and features using filters or kernels. In order to reduce computational complexity and improve feature translation invariance, pooling layers downsample the feature maps generated by convolutional layers. levels that are fully integrated process and carry out classification tasks using the high-level information retrieved by prior levels. CNNs are great at recognising faces, objects, and images because they can capture feature hierarchies spatially. Their hierarchical organization and ability to automatically learn features from raw input make CNNs very successful for a broad variety of image-related activities.

Photos processed using a convolutional neural network, a subset of deep learning models. There are several processing phases that images go through when they are input into a CNN. These stages include convolutional layers with filters, batch normalization layers, pooling layers, non-linear activations, and FC layers. H. Yanagisawa and colleagues (2018). A CNN model's trainable parameters are the complete connection weights and the convolution filter weights. A 256x256 input layer allows the proposed CNN model to handle 256x256 images. Multiple filters, each of which records a unique activation, are applied to the input image in a convolution layer. The linear convolution of a size FxF filter $k(m, n)$ with an image $x(m, n)$ yields activation $y(m, n)$,

$$y(m,n) = \sum_{i=-\frac{F}{2}}^{\frac{F}{2}} \sum_{j=-\frac{F}{2}}^{\frac{F}{2}} x(i,j)k(m-i, n-j) \text{ ------- (1)}$$

When K filters are applied to a volume with (X_1, Y_1, Z_1)-sized input, the resulting volume has dimensions (X_2, Y_2, K). Here's how to figure out X_2 andY_2,

$$X_2 = \frac{X_1 - F + 2P}{S} + 1 \text{ -------- (2)}$$

$$Y_2 = \frac{Y_1 - F + 2P}{S} + 1 \text{ ------- (3)}$$

values, represented by P for padding and S for striding. Here, they take on the roles of one and two, respectively. Following the convolution layers is the batch normalisation layer. Using the provided training data, this layer normalises the output of its predecessors. Each batch normalization layer is followed by an activation layer using ReLU. With each succeeding step, the output should shrink. Ten neurons make up the fc_1 layer, whereas three make up the fc_2 layer.

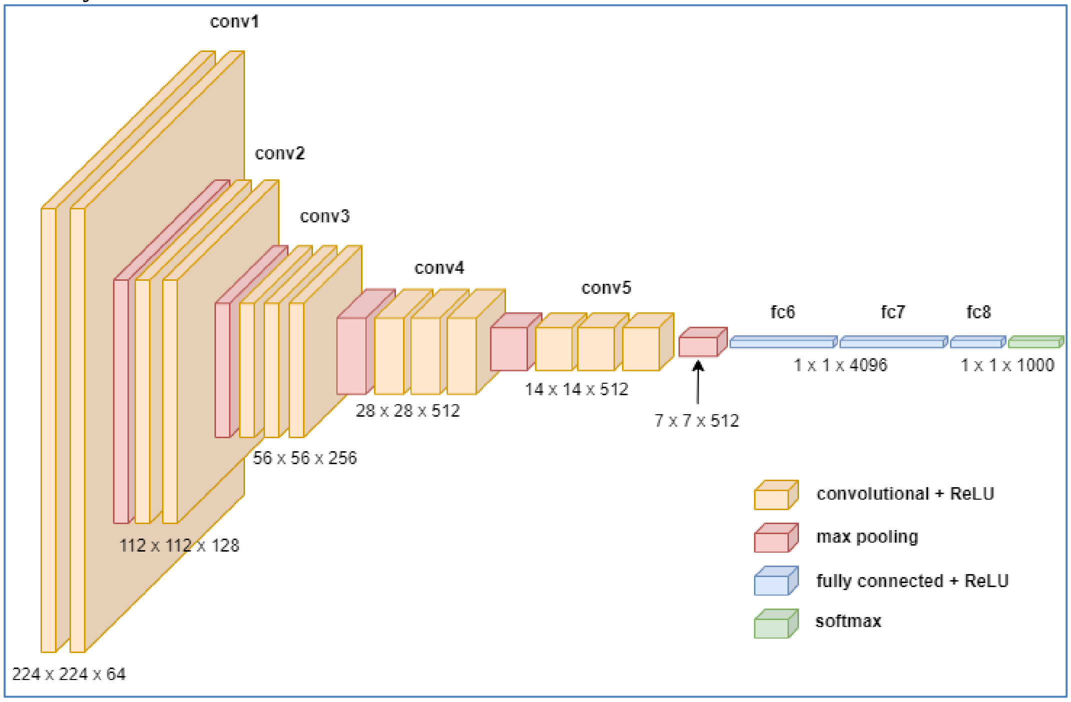

Figure 2: CNN architecture

The proposed CNN's memory requirements and computational complexity were carefully considered during development. Because of this limitation in the architecture, the CNN had to make do with fewer convolution filters and just two FC layers. The deep connections and convolution phases of the FC layer(s) are where a deep CNN model does the majority of its computations. To do convolution, one must multiply and add. The computations are therefore analogous to MAC operations, which stand for multiplication and accumulation. Opsconv is the number of MAC operations in a convolution layer, which is obtained by connecting the filter dimension $(\mathrm{F}_1, \mathrm{F}_2, \mathrm{K})$ with the output feature map dimension (X, Y, Z).

$\mathrm{O}_{\mathrm{ps}_{\mathrm{conv}}} = \mathrm{F}_1 * \mathrm{F}_2 * \mathrm{K} * \mathrm{X} * \mathrm{Y} * \mathrm{Z}$ -------- (4)

The weights of the FC layer are exactly proportional to the number of MAC operations executed at that layer (OpsFC). After adding up all the MAC operations carried out at each network layer, the total number of MAC operations executed by the whole network is equal to zero.

Algorithm 1: CNN
Input: • Input Skin image. Step: Convolutional Layer 1 (conv_1): $y(m,n) = \sum_{i=-\frac{F}{2}}^{\frac{F}{2}} \sum_{j=-\frac{F}{2}}^{\frac{F}{2}} x(i,j)k(m-i,n-j)$ Batch Normalization Layer 1 (bn_1). $X_2 = \frac{X_1-F+2P}{S} + 1$ ReLU Activation Layer 1 (relu_1). $Y_2 = \frac{Y_1-F+2P}{S} + 1$

Convolutional Layer 2 (conv_2): $O_{ps_{conv}} = F_1 * F_2 * K * X * Y * Z$ Softmax-based Classification Layer. **Output:** • The output is Skin Cancer types.

3.2.2 VGG-16

VGG16 uses smaller kernel sizes (33 in total) than AlexNet, which can explain why it performs better. One of the main selling points of VGGNet-16 is its design, which uniformly distributes 16 convolutional layers [Fig. 3]. Several features, such as 3x3 convolutions and filters, are shared with AlexNet.

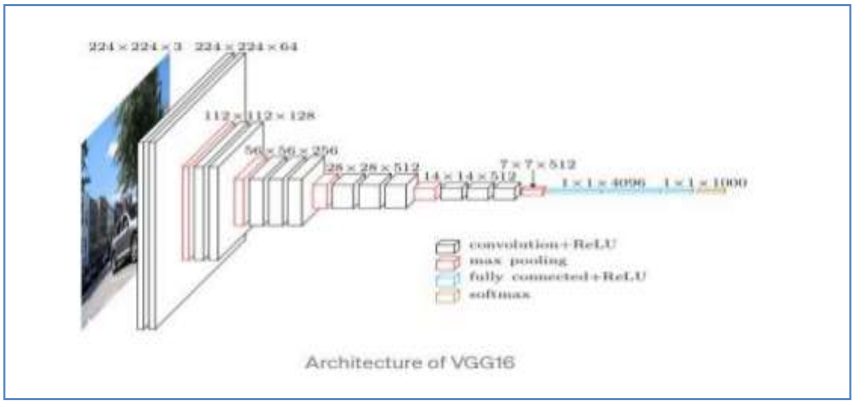

Figure 3: VGG 16

To create this model, only two training epochs were used. The VGG-16 model's accuracy and loss as a function of time are shown in Figure [3]. The Y-axis represents epochs. An epoch is a temporal unit that stands for the whole of a dataset for a single cycle. The model's validation error (Val loss) becomes less as time goes on. In a single session, all components of the model get the whole dataset in advance while remaining hidden. Data for a whole epoch couldn't possibly be input all at once, so we partitioned it into 32 smaller time periods. We found that a sample size of 32 gave us the most accurate results when running our model. Until all data has been processed by the model, the batch size of 32 samples will ensure that only the most recent samples are used for training.

Learn how to change a pre-trained convolutional neural network's (CNN) last two layers using a transfer learning method in this article. Distributing CNN models with 16 or 19 layers is the specific goal of VGG-16. When compared to the industry standard, the VGG-16 is just slightly behind. But they work rather well for classifying images, and they might provide the groundwork for models that use images as input in the future. We use this library to identify bird species since TensorFlow runs in the background while VGG-16 is running. Given the abundance of characteristics provided by VGG-16 is used for classification purposes. The sixteen-layer VGG network was used. Before being employed in VGG-16's training procedure, the input pictures are up-scaled to a 224x224 resolution.

Algorithm 2: VGG 16
Input: **Input Image** **Step:**

1. **Load Pre-trained VGG16 Model**: load the pre-trained VGG16 model along with its weights and architecture. deep learning frameworks like TensorFlow or PyTorch to do this.
2. **Preprocess Input Image**: preprocess the input image to ensure it matches the format expected by the VGG16 model. This typically involves resizing the image, normalizing pixel values, and possibly converting it to a suitable color format (e.g., RGB).
3. **Forward Pass Through VGG16**: perform a forward pass of the preprocessed input image through the VGG16 model. This means passing the image through the network layer by layer, applying convolution, activation, and pooling operations.
4. **Feature Extraction**: As the input image propagates through the VGG16 layers, feature maps are generated at different layers. These feature maps represent increasingly abstract and hierarchical features of the input image. extract these feature maps at the desired layer(s) to obtain informative features.

Output:

1. **Extracted Features**: The output of the feature extraction process is a set of feature maps or feature vectors obtained from one or more layers of the VGG16 network. These extracted features capture different levels of visual information from the input image.

3.2.3 Resnet

One design of deep neural networks that shook up computer vision and picture identification was ResNet, which stands for Residual Network. Created in 2015 by Microsoft Research, ResNet tackles the issue of disappearing gradients in very deep neural networks by introducing the notion of residual learning. One of ResNet's most revolutionary features is the use of skip connections, often called residual connections, which allow the network to skip over certain levels and link information from early layers straight to subsequent ones. This makes it possible to train deeper networks without sacrificing accuracy. Multiple residual blocks make up ResNet architecture. Each residual block generally has activation functions, batch normalization, multiple convolutional layers, and skip connections. With the help of skip connections, the network can learn residual mappings, which improve its training efficiency and overall performance on tasks like semantic segmentation, object identification, and picture classification. A leading deep learning architecture for computer vision, ResNet has quickly risen to prominence because to its efficacy and adaptability.

In particular, the input is normalized using a label encoder. Labels that do not have numbers are replaced with their numerical counterparts. Tokenize takes TF-IDF, word counts, or word frequencies as input and turns them into integer sequences or vectors with binary coefficients.

The total token frequency, abbreviated asTf, is the count of token appearances in a certain content record. As a proportion of all tokens, this token's frequency in the content record is given by equation 5.

$$Tf_{ij} = \frac{n_{ij}}{\sum_k n_{ij}} \text{------ (5)}$$

To determine how often out-of-the-blue tokens show up in archived records, statisticians use the Inverse Data Frequency (idf) statistic. It's more likely that the tokens that only occur seldom in the record document (i.e.2)

$$\mathrm{df(w)} = \log\left(\frac{\mathrm{N}}{\mathrm{df_i}}\right) \text{------- (6)}$$

A word's TF-IDF score (w) is calculated by adding its TF score (3) to its IDF score (w) (7). Specifically, I refer to the following equation 7,

$W_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right)$ ------- (7)
$tf_{i,j}$= counting the occurrences of I in j
df_i= records where I is the id value
N = the whole count of files

Tokens are converted to word sequences using the text to sequence tool, which is then used to train the model.

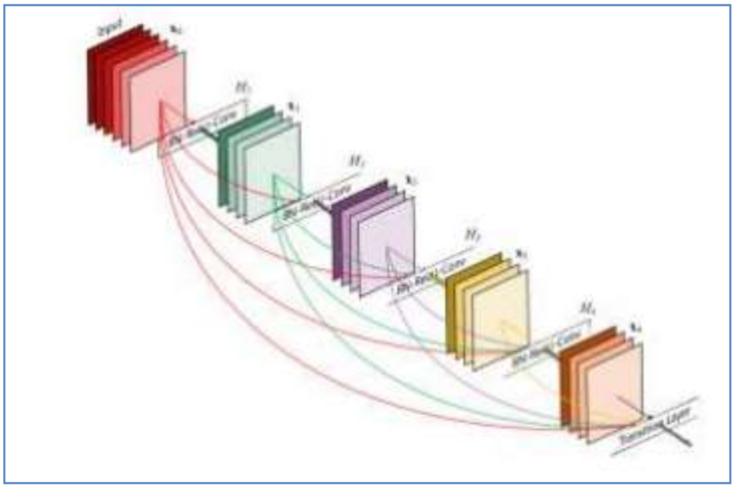

Figure 4: ResNet architecture

3.3 Skin Condition Analysis

Using image processing methods, especially machine learning algorithms, skin condition analysis evaluates and diagnoses a range of skin problems. Obtaining skin pictures, such as photos or digital scans, is the first step in this method. Prior to analysis, these photos undergo preprocessing procedures to improve their quality. Images' texture, colour, and form are among the significant patterns and qualities that are sought after using feature extraction algorithms. Next, labelled datasets are used to train machine learning algorithms, such as convolutional neural networks (CNNs), to categorise the characteristics that have been retrieved and to forecast the existence of certain skin disorders. Individuals looking for customised skincare treatments, dermatologists, and other healthcare providers can all benefit from the analysis's findings. Improved diagnosis and treatment of a wide range of dermatological problems are made possible by the use of image processing for skin condition analysis, which allows for non-invasive, efficient, and accurate evaluations.

IV. Results and discussion

This section represents to elucidate the key findings of the study and to provide insights into their broader implications for the field of skin care detection using image processing techniques.

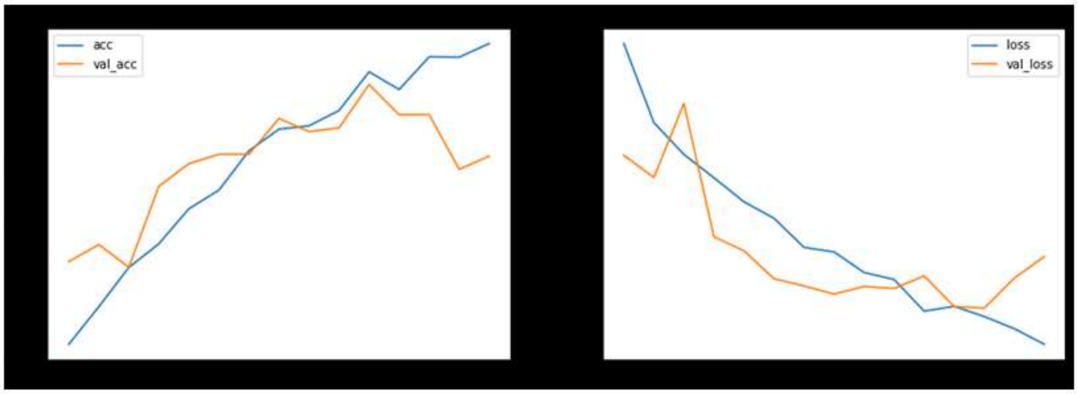

Figure 5: Training and testing accuracy comparison chart

The figure 5 represents training and testing accuracy comparison chart the x axis shows epochs and the y axis shows training and testing accuracy.

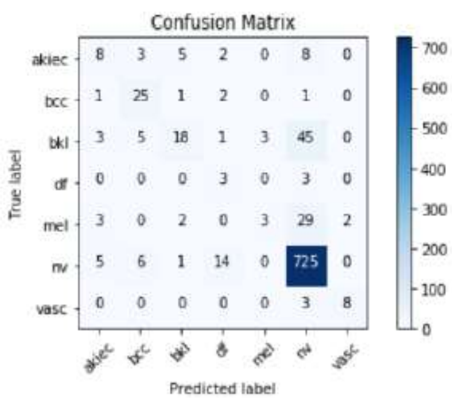

Figure 6: Confusion matrices

Figure 7: Skin disease prediction

Figure 7 illustrates the skin disease prediction process using the developed methodology. The figure shows a flowchart depicting the sequential steps involved in predicting skin diseases from input skin images. Initially, raw skin images are fed into the system, where they undergo preprocessing steps such as noise reduction and image enhancement.

Figure 8: Skin image input page

Figure 8 depicts the skin image input page, which serves as the interface for users to upload or capture skin images for analysis in the proposed skin care detection system. The user interface is designed to be intuitive and user-friendly, with options for uploading existing skin images from local storage or capturing new images using a device's camera. The input page can include features such as image preview, file upload buttons, and camera access permissions.

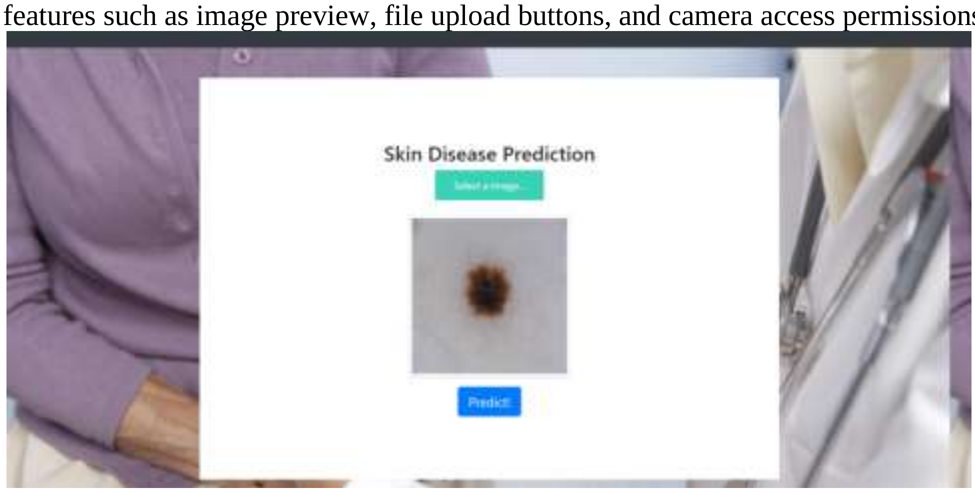

Figure 9: Skin disease predicted

Figure 9 displays the outcomes of skin disease prediction achieved through the implemented methodology. The figure showcases a graphical representation or tabular format presenting the predicted skin diseases along with corresponding confidence scores or probabilities. Each predicted skin disease is listed alongside its likelihood of occurrence, providing insights into the accuracy and reliability of the prediction.

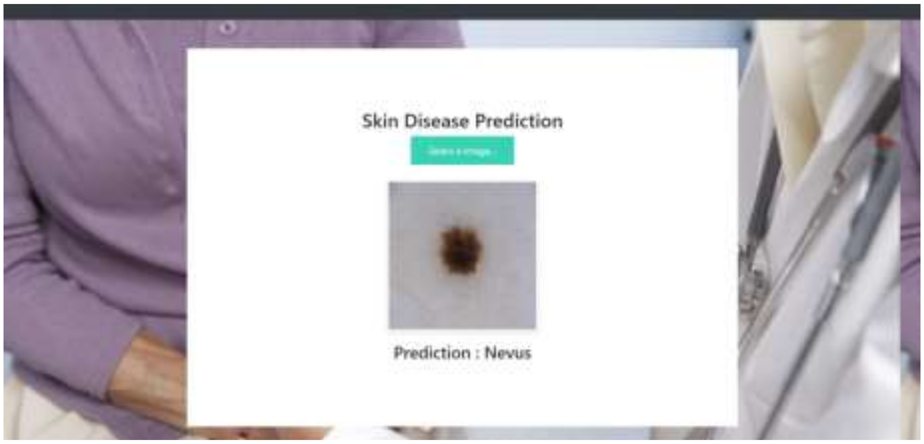

Figure 10: Disease name prediction

Figure 10 illustrates the disease name prediction results obtained from the implemented methodology. The figure presents a list or visualization of the predicted disease names corresponding to the skin conditions identified through the analysis of input skin images. Each disease name is associated with a confidence score or probability, indicating the model's level of certainty in its prediction.

V. Conclusion

In conclusion, the development and evaluation of a multi-model neural network system for skin cancer detection, integrating CNN, VGG16, and ResNet architectures, showcase a promising step forward in leveraging the strengths of diverse deep learning models. The fusion of these models enhances the overall performance in accurately identifying and distinguishing between malignant and benign skin lesions. The experimental results demonstrate that the combined features extracted from different architectures lead to improved sensitivity and specificity compared to individual models. The integration of CNN, VGG16, and ResNet not only addresses the limitations of each model but also contributes to a more robust and comprehensive representation of complex patterns inherent in skin cancer images. The interpretability of the multi-model system is a crucial aspect, as it provides insights into the decision-making process. This transparency is essential for gaining the trust of medical professionals and end-users, promoting the adoption of deep learning models in clinical settings. While the presented approach shows promising results, it is essential to acknowledge potential challenges and avenues for future research. Further exploration could involve fine-tuning hyperparameters, incorporating additional data augmentation techniques, and expanding the dataset to ensure the model's generalizability across diverse populations and skin types.

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