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Skin Cancer Detection Using Deep Learning

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Abstract:

Cancer is a deadly disease that arises due to the growth of uncontrollable body cells. Every year, a large number of people succumb to cancer and it's been labeled as the most serious public health snag. Cancer can develop in any part of the human anatomy, which may consist of trillions of cellules. One of the most frequent type of cancer is skin cancer which develops in the upper layer of the skin. Previously, machine learning techniques have been used for skin cancer detection using protein sequences and different kinds of imaging modalities. The drawback of the machine learning approaches is that they require human engineered features, which is a very laborious and time-taking activity. Deep learning addressed this issue to some extent by providing the facility of automatic feature extraction. In this study, convolution-based deep neural networks have been used for skin cancer detection using ISIC public dataset. Cancer detection is a sensitive issue, which is prone to errors if not timely and accurately detected. The performance of the individual machine learning models to detect cancer is limited. The combined decision of individual learners is expected to be more accurate than the individual learners. The ensemble learning technique exploits the diversity of learners to yield a better decision. Thus, the prediction accuracy can be enhanced by combing the decision of individual learners for sensitive issues such as cancer detection. In this paper, an ensemble of deep learners has been developed using learners of VGG, CNN, and ResNet for skin cancer detection. The results show that the combined decision of deep learners is superior to the finding of individual learners in terms of sensitivity, accuracy, specificity, F-score, and precision. The experimental results of this study provide a compelling reason to be applied for other disease detection.

Keywords: VGG, CNN, ResNet, Violence Identification, Deep Learning, OpenCV, Firebase, JSON.

1. Introduction

The Skin Cancer Detection project is dedicated to the creation of a cutting-edge technology for the early finding and determining skin conditions of cancer. Skin cancer occurs often and potentially fatal illness, and early identification is critical for effective treatment and improved patient outcomes. This research intends to use cutting-edge technology such as computer vision and machine learning to develop a robust and reliable system that can assist doctors to identify and categorize skin lesions linked with skin cancer. Skin cancer is a global health concern, with its incidence steadily rising over the years. Timely finding and determining skin conditions cancer are crucial to prevent its progression and ensure prompt intervention. Traditionally, dermatologists rely on visual examination and manual analysis of skin lesions to determine their malignant potential. However, this process can be challenging and subjective, leading to variations in accuracy and potential diagnostic errors. The integration of technology and artificial intelligence has the potential to enhance diagnostic capabilities and support healthcare professionals in making informed decisions. The major goal of the Skin Cancer Detection project is to create an automated system capable of detecting and classifying skin cancer based on photographs of skin lesions. The system's goal is to give dermatologists with a dependable tool that will aid in precise diagnosis, increase efficiency, and minimize the danger of misdiagnosis. By leveraging advanced technologies, the project seeks to contribute to early detection, enable timely interventions, and ultimately improve patient outcomes in the management of skin cancer. The Skin Cancer Detection project intends to provide an enhanced technique for detecting skin cancer and diagnosis. The project aims to give dermatologists with an automated tool that may aid in correct diagnosis and enhance the efficiency of skin cancer detection by merging computer vision and machine learning techniques. We want to contribute to the early detection of skin cancer, promote prompt therapies, and eventually enhance patient outcomes in the management of this common illness through this initiative.

2. Literature Survey

Ammara Masood et.al. Statistics and performance from the most significant implementations recorded to yet were provided. They tested the efficiency of numerous classifiers designed particularly for skin lesion diagnosis and discussed the results. Whenever possible, indications of various factors affecting the technique's performance are provided. They provide a framework for comparing skin cancer diagnostic models and examine the findings based on these models. The shortcomings of certain previous studies are noted, and suggestions for more research are made. [1]

Nazia Hameed et.al. Studied instance of the art in computer assisted diagnostic systems and assessed recent practices in key phases of these systems. Statistics and outcomes from the most recent and significant deployments are reviewed and presented. They compared the performance of recent work based on various parameters such as accuracy, dataset, computational time, color space, machine learning technique, and so on, and summarized it in table format for the benefit of emerging researchers in the discipline of computer aided skin diagnosis systems. The research problems associated with the various components of computer-aided skin cancer diagnostic systems are also discussed. [2]

Maciej Ogorzałek et.al. The approach for Computer Assisted Detection and Classification of Skin Lesions that has been proposed for Diagnostic Support combines medical experience with several cutting-edge technologies, including image processing, pattern classification, statistical learning, and ensembling techniques of model-based classifiers. Furthermore, the suggested approach demonstrated excellent results, with correct classification of up to 98% of cases.[3]

Fabio Santos et.al. Centered on the current state of automated skin lesion diagnosis, while also providing a comprehensive view into the challenges and opportunities in dermatology care. [4]

Shetu Rani Guha et.al. developed a machine learning-based approach for diagnosing seven kinds of skin disorders using CNN. The 2018 International Skin Imaging Collaboration (ISIC) dataset was used to improve classification accuracy by combining transfer learning and CNN. When compared to CNN alone, transfer learning has been proven to increase accuracy by 11%. The performance of this proposed approach is promising when compared to earlier attempts.[5]

A D Mengistu et.al. suggested a digital image processing approach to detect and forecast the different forms of skin malignancies utilizing digital image processing techniques. The categorization system was monitored and corresponded to specified classifications of skin cancer. Combining Self organizing map (SOM) with radial basis function (RBF) for skin cancer classification and diagnosis outperforms KNN, Nave Bayes, and ANN classifiers. It was also demonstrated that morphology's discriminating capability www.ijcrt.org IJCRT2106191 International Journal of Creative Research Thoughts (IJCRT) www.ijcrt.org 2021 IJCRT | Volume 9, Issue 6 June 2021 | ISSN: 2320-2882 b526 Color characteristics outperformed texture features, however when morphology, texture, and color features were combined, classification accuracy rose. [6]

Uzma Bano Ansari and colleagues presented a sum-based skin cancer detection method for early identification of skin cancer illness. Image processing technologies and the Support Vector Machine (SVM) algorithm used in the diagnosis procedure. The dermoscopy picture of skin cancer is captured and subjected to a variety of pre-processing procedures for noise reduction and image enhancement. Following that, the picture is segmented using the Thresholding approach. Some picture characteristics must be retrieved using GLCM approach. These characteristics are sent into the classifier. Support vector Machine (SVM) is a classification algorithm. It determines if the picture is malignant or non-cancerous. [7]

Enakshi Jana et al. conducted a thorough literature review of current skin cancer detection technologies, as well as an accurate comparison of state-of-the-art algorithms. A comprehensive literature review of current skin cancer detection techniques is conducted. SVM and Adaboost offer the greatest results of any skin cancer detection approach. A survey and study of the many forms of ANN architecture and utilization of SVM for skin cancer picture classification, in addition its accuracy and performance, are presented. A brief summary of Melanoma's operation and detection is provided, which is essential for classifying normal and malignant skin cells. [8]

Ammara Masood and colleagues introduced a semi-supervised, self-advised Melanoma learning model for automated analysis detection using dermoscopic pictures. Deep belief architecture is built with labeled and unlabeled data, and fine tuning is done with an exponential loss function to optimize labeled data separation. A self-advised SVM method is employed in parallel to improve classification results by mitigating the influence of misclassified data. To improve generalization and redundancy, polynomial and radial basis function-based SA-SVMs and Deep networks are trained using training samples picked at random using a bootstrap approach. After that, data are combined using the least square estimate weighting method. The suggested model is validated using 100 dermoscopic pictures. When compared to other prominent classification approaches, the suggested model employing deep brain processing surpasses most of them, including KNN, ANN, SVM, and semi-supervised algorithms like Expectation maximization and transductive SVM.[9]

In contrast to conventional medical personnel-based detection, Vijayalakshmi M M et al. proposed a wholly automated approach of dermatological disease recognition from lesion photographs. Our model is divided into three stages: data gathering and augmentation, model creation, and prediction. We combined different AI techniques, such as Convolutional Neural Network and Support Vector Machine, with image processing tools to build a superior structure, resulting in an precision of 85%. [10]

Suleiman Mustafa and colleagues suggested an automated approach for identifying melanoma skin cancer using simple pictures of afflicted skin patches. They first use the GrabCut method to segment an input picture into lesions of interest that appear to be melanoma, and utilize image processing methods after that to extract attributes such as form, color, and geometry. Using a SVM and RBF, these extracted characteristics are classified as cancerous "malignant" or non-cancerous "benign" moles.[11]

Shalu et al. created a method for detecting melanoma skin cancer based on a MED-NODE dataset of digital photographs. Because the raw photos in the collection contain numerous artifacts, preprocessing is used first to eliminate these artifacts. The Active Contour segmentation approach is then utilized to extract the region of interest. The segmented component was used to extract various color characteristics, and effectiveness of the system was assessed using three classifiers (Nave Bayes, Decision Tree, and KNN). The system outperforms other classifiers with an accuracy of 82.35% on Decision Tree. [12]

Gaana M. and colleagues employed image capture, pre-processing, segmentation, noise reduction, and feature extraction. They used Cubic Regression to apply Supervised Machine Learning for the first time. The system was instructed using this approach to display the stages of skin cancer as Benign, Melanoma, and Melanoma automatically. [13]

Using MSVM, R.S. Shiyam Sundar et al. suggested a unique approach for early diagnosis of melanoma. The five different forms of skin lesions include solar keratosis, also known as actinic keratosis, basal cell cancer, neviocytic nevus, squamous cell cancer, and seborrheic verruca. The recommended method uses an automated process in which the query photographs are sorted and matched with greater likely kinds in order to categorize the type of melanoma. Data classification may be accomplished well with the multi class support vector machine. The algorithm is built utilizing certain training samples and a stage-by-stage learning process. Here, gradient, contrast, and edge features of color and texture are recovered. For testing and classification, the proposed system contains an image database with images of each of the five types of melanoma. The recommended support vector machine technique has the greatest accuracy of all five options, according the simulation results. [14]

Zahra Waheed et al. Reported an effective ML method for detecting melanoma in dermoscopic pictures. Based on its discriminating qualities, it identifies melanoma skin lesions. The suggested technique begins by extracting several types of color and texture information from dermoscopic pictures based on distinct structures and changing intensities of melanocytic lesions. The retrieved characteristics are then given into the classifier to classify melanoma from dermoscopic pictures in the second stage. The paper also discusses the relevance of color and texture cues in the identification of melanomas. The proposed technique is evaluated in terms of accuracy, sensitivity, specificity, and Area under the ROC curve (AUC) using the publically available PH2 dataset. It is discovered that employing extracted characteristics, good outcomes are attained, showing the correctness of the suggested approach.[15]

3. Existing And Proposed Work

3.1 Existing Work

- This effort might lead to a way for identifying melanoma carcinoma utilizing image processing methods.
- In this input, the system is that skin lesion image, and it analyzes the existence of carcinoma using image processing algorithms.
- The lesion is image to analysis tools checks as different Melanoma in parameters, color, area perimeter, diameter to texture, size to form analysis for image segmentation and the feature stages.
- The derived feature parameters used to identify the picture as Non-Melanoma or Melanoma cancer lesion.

3.2 Proposed Work

- This study might result in a procedure for melanoma detection carcinoma utilizing image processing methods.
- In this input, the system is that skin lesion image, and it analyzes the existence of carcinoma using image processing algorithms.
- Tools for image analysis are used to assess several Melanoma parameters including as color, area peri-

meter, diameter, texture, size, and form for image segmentation and feature phases.

- The derived feature parameters will not distinguish between Non-Melanoma and Melanoma cancer lesions. We are collecting patient data following therapy through poll.

4. Methodology

4.1 Data Collection

- Dataset used for this are extracted from Kaggle towards skin cancer Detection.
- It consists of 10000 images of skin cancer.
- The training data consists of 8000 images and testing data consists of 2000 images.

Figure 1: Images of Skin Cancer

4.2 Deep Neural Network

In order to develop the proposed ensemble, three different convolution-based deep neural network models of VGG, CNN, and ResNet have been developed. Architectural development information of the models are described below:

4.2.1 VGG16

Among the most popular used CNN models is VGG. The reason for the popularity of the VGG model is; its easiness, simplicity, and the use of small-sized convolutional kernels that make the VGG model a popular deep learning model. In order to removing and classification of features, the VGG architecture employs a 3 × 3 convolution kernel with max-pooling and ReLU layers, as well as three fully linked layers. The use of smaller kernels in the design helps in fewer amount of parameters and, as a result, more efficient training and testing. Furthermore, the effective receptive fields can be expanded to bigger values by stacking a sequence of 3 × 3 sized kernels (e.g. 5 × 5 with two layers, 7 × 7 with three layers, and so on). Most crucially, smaller filters allow more layers to be stacked, resulting in a deeper network and higher performance on vision tasks. This effectively conveys the architecture's central notion, which encourages the use of deeper networks for better feature learning. The VGG model layer consists of five blocks after the input layer. In the proposed model, at the input layer VGG model reads pre-processed images of size 224 × 224. After the input layer, the first block of the layer starts containing 2 convolutional layers followed by the pooling layer. The initial convolutional layer is made up of 64 filters. Following polling, the resulting picture shrinks to 112 112. Each layer block has a nearly identical layer layout. In the second block, features are shrunk to a size of 56 ×56 after a first and second convolutional layer with 128 filters. The feature map is reduced to 28 28 in the third block by max-pooling three convolutional layers with 256 filters. The fourth block likewise comprises three convolutional layers with 512 filters and a pooling layer, which reduces the size of the feature map to 14 × 14 pixels. The fifth and the last block has three convolutional with the 512 filters followed by the pooling layer that further reduces the feature map to 7 × 7. The VGG detailed architecture is in Fig. 2

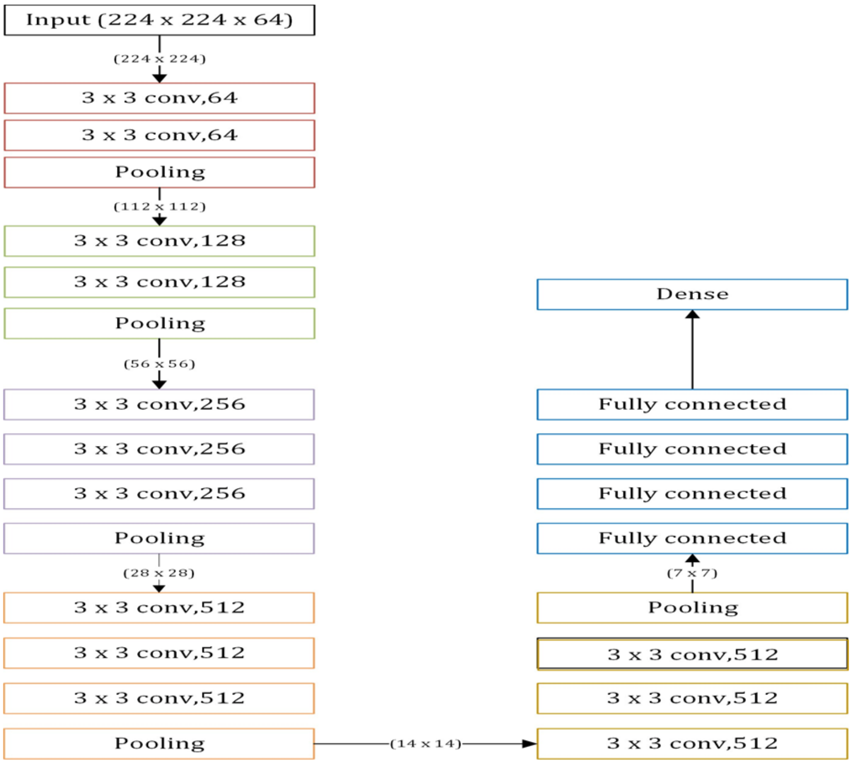

Figure 2: VGG16 Block Diagram

4.2.2 ResNet

The DNN model incorporates residual learning. The model's most essential components are the convolution and pooling layers, which are completely coupled and placed one upon the other. The Residual Network is distinguished from the standard network by the identity connection between its tiers. The residual block of the ResNet is depicted in Fig.3, to bypass one or more in the strata of ResNet, it introduces the "skip connection" and "identity shortcut connection" in the system. The detailed architecture of deep residual network (ResNet) is presented.

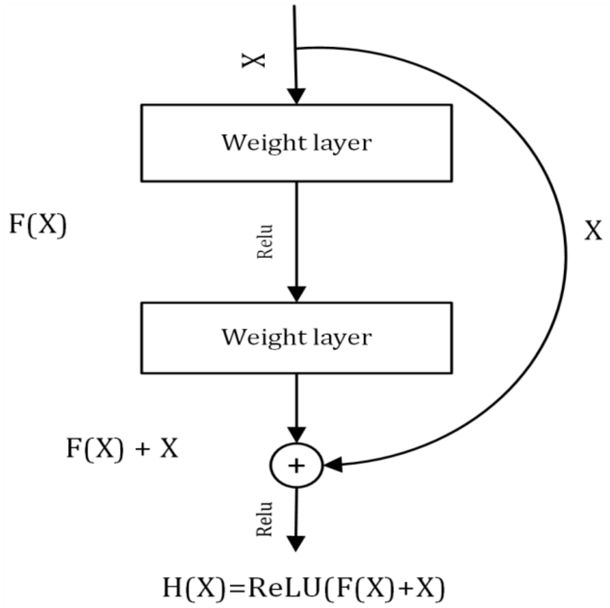

Figure 3: Structure of Residual Block

5. Results And Discussion

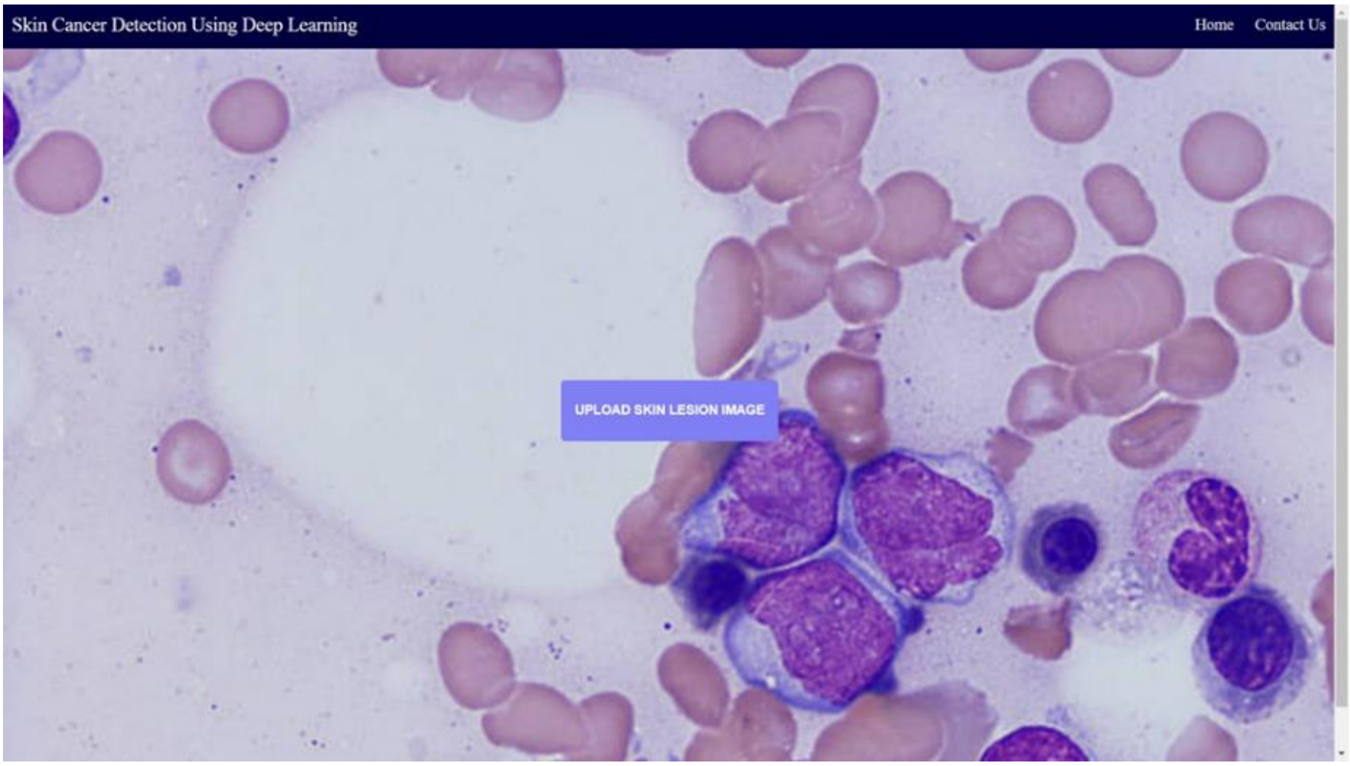

Figure 4: Home Page

Figure 5: Positive Result of Uploaded Image

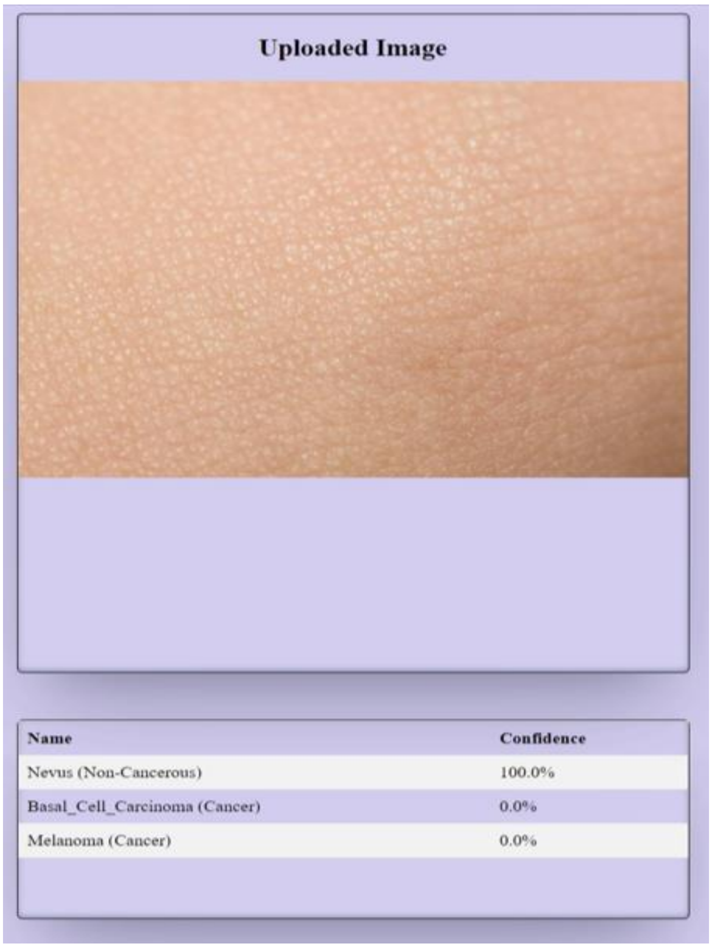

Figure 6: Negative Result of Uploaded Image

5.1 Different Measure Used To Evaluate Performance

5.1.1 Accuracy

The classifier's ability to properly anticipate the class labels is measured by accuracy. It's calculated as follows:

$$\text{Accuracy} = \frac{(\text{TN} + \text{TP})}{(\text{FN} + \text{FP} + \text{TN} + \text{TP})} \quad \text{----------} \quad (1)$$

5.1.2 Sensitivity

The most used parameters in epidemiological and medical research are sensitivity and specificity, however most statisticians in mathematical domains are ignorant of them. It evaluates the classifier's ability to predict the positive class properly. The sensitivity value is computed as follows:

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{FN} + \text{TP})} \quad \text{----------} \quad (2)$$

5.1.3 Specificity

The classifier's ability to properly predict the negative class is measured by specificity. The term specificity is defined as follows:

$$\text{Specificity} = \frac{\text{TN}}{(\text{FP} + \text{TN})} \quad \text{----------} \quad (3)$$

5.1.4 F-Score

The statistical tests are evaluated using the F-score. F-score uses Recall and Precision to calculate prediction accuracy. The F-score may also be calculated using the weighted average of recall and accuracy. The recall is obtained by dividing the number of correct guesses by the total number of predictions. Precision is calculated by dividing the number of correctly predicted forecasts by the number of predictions returned. The F-score is determined as follows:

$$\text{F-Score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \quad \text{----------} \quad (4)$$

Where, $\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})}$ while $\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})}$

5.2 A Graph Comparison of Accuracy Performance Between Presented Approach and Various Deep Learning Model

5.2.1 VGG16

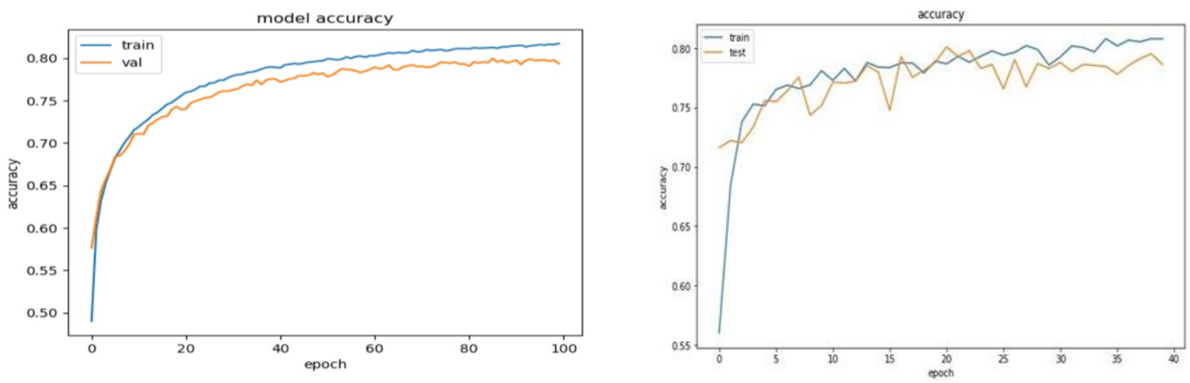

Figure 7: Accuracy of VGG16

5.2.2 ResNet

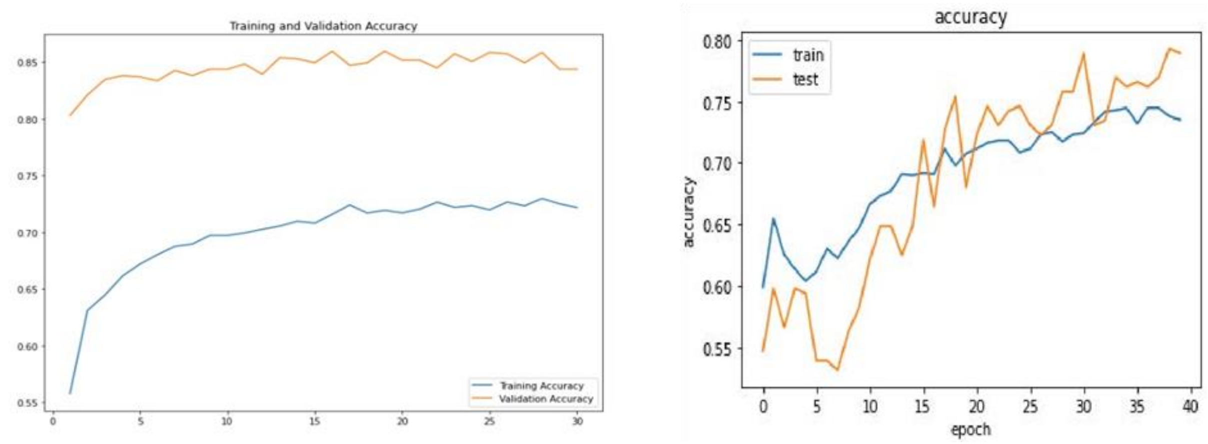

Figure 8: Accuracy of ResNet

5.3 A Graph Comparison of Accuracy Performance Between Presented Approach and Various Deep Learning Model

5.3.1 VGG16

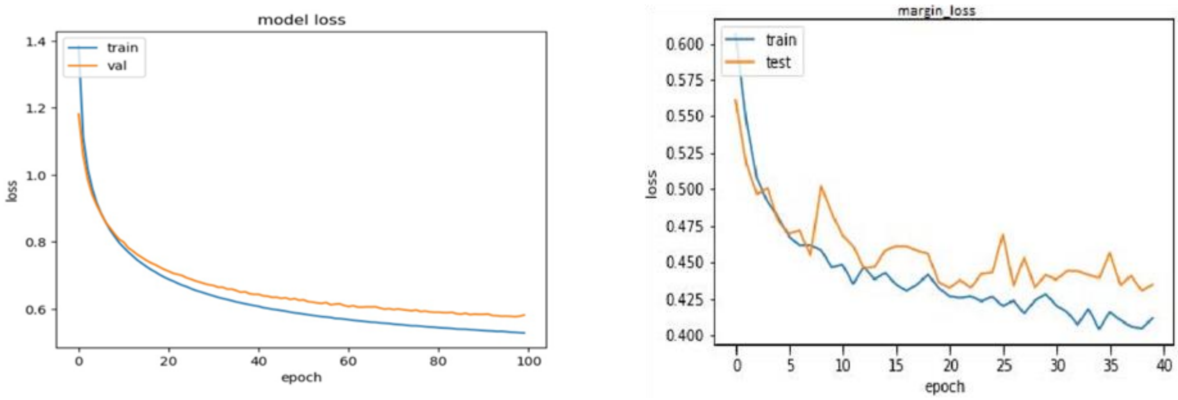

Figure 9: Loss of VGG16

5.3.2 ResNet

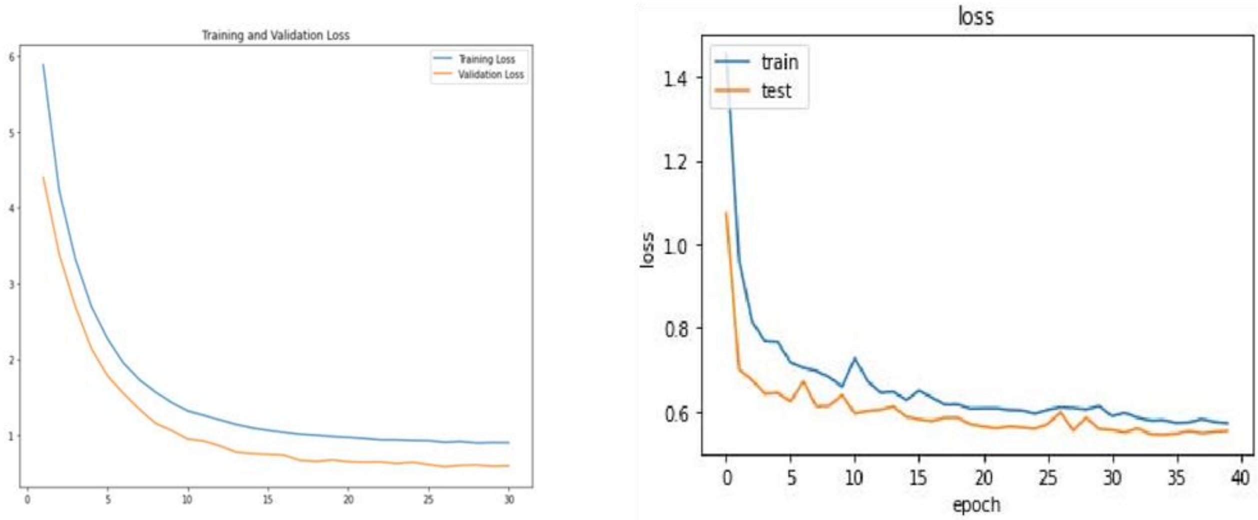

Figure 10: Loss of ResNet

By viewing an above Fig.7 and Fig.8 we can clearly say that the accuracy of proposed module is better than the accuracy of existing module. The proposed module is performed better compare to existing

module. And also Viewing an above Fig.9 and Fig.10 the loss of data during testing and training is better in proposed module compared to existing module.
On viewing all of the above Fig.7, Fig.8, Fig.9, Fig.10 we can clearly say that the our proposed module was for better than the existing module. Because, the performance of proposed module is too good when compare to the existing module.

6. Conclusion

The most common cause of mortality from skin cancer is a malignant lesion. If it is discovered early on, therapy may be feasible. In the literature, DL methods have been used to detect cancer, however the effectiveness of each individual learner is limited. The performance can be enhanced by combining the decision of diverse individual learners for decision-making on sensitive issues such as cancer. This paper developed an ensemble model to detect skin cancer. It is created by integrating three deep learning models: VGG, CNN, and ResNet. The findings show that the suggested ensemble attained an average accuracy of 95% with classification training. In terms of quality criteria like as sensitivity, accuracy, F-Score, specificity, and precision, the suggested model outperforms individual learners. In future, we will consider a large skin lesion image dataset with more classes. Further work will focus on designing an ensemble model to enhance the classification performance as well as extending the CNN architectures to different kinds of skin lesions such as eczema and psoriasis. Another intriguing avenue would be to examines more enhanced DL models for skin lesion diagnosis. In the future, we hope to examines the efficacy of reinforcement learning-based systems for skin cancer diagnosis.

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