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REVOLUTIONIZING DERMATOLOGY: ADVANCED DEEP LEARNING TECHNIQUES FOR AUTOMATED SKIN DISEASE DETECTION

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ABSTRACT
Skin is the largest tissue in the humanoid body, and it protects body from external damage, regulates body temperature, and provides the sense of touch. It is made up of three layers: the epidermis, dermis, and subcutaneous tissue. Skin cancer is a disorder in which tissue cells grow abnormally and would extent to additional portions of body. It is typically caused by solar system or tanning bed exposure to ultraviolet (UV) radiation. Early detection of skin cancer is crucial because it increases the likelihood of successful cure and treatment. Although advanced stages of the disease are more difficult to treat and have a worst diagnosis. Regular skin self-examinations, combined with professional skin checks, can aid in the early detection of skin cancer. Machine learning has been used for detection of skin cancer. But it works on features, for which we must first extract the features from the raw data. Feature engineering is a time consuming and challenging task. Deep learning is an emerging area and subfield of artificial intelligence, which extracts useful features from raw data on its own. But it is quite time-consuming task to train such complex deep learning methods and requires huge computational resources. In this work, we have proposed a deep learning model based on ensemble learning for detection of skin cancer. In this model, we used the ensemble learning method for combining four different popular CNN ***architectures*** *namely InceptionV3, ResNet50, Efficient net and Xception. In this study, we use HAM10000 dataset for our experiments. First, when we train these classifiers, our proposed model was not performing better due to presence of unbalancing in the data. After balancing the dataset, our proposed model was performing better in terms of accuracy, precision, recall and F1-score. On balanced dataset, our proposed model gave an accurate score of 0.94, Precision score of 0.93, Recall and F1-score of 0.94.*

Keywords—Skin Cancer, Machine Learning, Deep Learning, HAM10000 dataset, Medical Imaging, Convolutional Neural Networks (CNN), Cancer Diagnosisy

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Introduction

Skin is an essential organ in the human body. Skin protects our internal organs from germs and other dangerous bacteria and viruses. Skin disorders are complicated and diagnosing them can be challenging for a dermatologist. It can be classified into two types: melanoma and non-melanoma [1]. Melanoma is a very deadly kind of skin cancer. Melanoma skin cancer affects the human epidermis. Many lives can be saved if skin cancer is detected early [2]. Melanoma is a form of skin cancer which develops from cells in the skin that produce pigment (color). It can appear anywhere on the body, but it is most found on sun exposed areas such as the face, neck, arms, and legs [3]. Melanoma is less common than non-melanoma skin cancers, but it is more dangerous because it can extend to additional portions of the body. However, complex algorithms and equipment are necessary for expert decision making in this respect. Non-melanoma skin cancer refers to a type of skin cancer that develops from the skin's cells [4]. (BCC) Basal cell carcinoma [5] and (SCC) squamous cell carcinoma [6,7] are the two most common types of non-melanoma skin cancer (SCC).

Melanoma Skin Detection: Melanoma is a dangerous lesion and disease that is malicious format of cancer that occurs in the melanocytes [1,8,9], the cells in the skin that produce dye. Non-melanoma skin cancer encompasses all non-melanoma melanomas, such as squamous cell carcinoma and basal cell carcinoma. Early detection of this dangerous disease melanoma and non-melanoma skin cancer is essential for early intervention and treatment, which can significantly improve the disease's prognosis. Some common methods for detecting melanoma and non-melanoma skin cancer are as follows: Visual Inspection: Visual inspection [12] is the simplest and easiest way to detect the melanoma. It requires field knowledge. Medical specialists and Dermatologists use this to examine the skin for any unusual growth, spots, or color or shape changes. Biopsy: A biopsy [13] may be performed if a suspicious lesion is found during a visual examination.

Imaging Tests: Ultrasound, MRI imaging and CT scan tests could be used to figure out the extent of cancer and whether it has spread to other areas of the body. Blood Tests: Blood tests can be used to have as of certain based clustering [14,15] to melanoma or non-melanoma skin cancer.

I. Literature review

Deep learning and machine learning and its utilization in different areas of research for skin cancer detection. [37,38] Claim that VGG-16 has many parameters. Due to this large number of parameters, the detection of VGG-16 is affected. They modified the VGG-16 network. They leave the first three blocks unchanged. But they removed the convolutional layer from third layer. They introduced a batch normalization layer after each pooling layer. They also introduced a Global Average Pooling layer at the end, because it avoids dense layers that is made-up of fully connected neurons. [39,40] Worked on determining whether there is melanoma in the image or not. They used artificial neural networks for classification, which is trained based on backpropagation algorithm. Inside their dataset, there were a total of 90 dermoscopic images. They extract the useful features from the dataset by using gray level co-occurrence matrix. For thresholding they used maximum entropy. They achieved an accurate score of 86.66. [41] Proposed a model for detecting, whether the skin tissue is cancerous or non-cancerous. They also used ANN for classification, which they trained on backpropagation algorithm. They used a total of 60 images for training their model, in which 30 images were of cancerous tissues and 30 22 were non-cancerous tissues. [42] Proposed a model for detecting whether this skin tissue is common mole, non-common mole or melanoma. The model used for this work was feed forward Back propagation neural network. They used 200 dermoscopic images. They extracted features from these images using ABCD rule. They achieved an accurate score of 97.51. [43] Classified skin cancer disease into either malignant or benign tissues. They used the Caucasian race and Xanthus race dataset. From the

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images, they extracted lesion features based on self-generating neural network. [44] Proposed a model for the detection of skin lesions. They performed first preprocessing to enhance the quality of images. In the preprocessing, their main aim is to remove the hair from the skin lesions, for which they applied adaptive principal curvature to detect the hairs and for removing these hairs they used inpainting method. For further improving the quality, they use color normalizations for improving the thresholding segmentation quality. [45] Proposed a model, called InSiNet that was based on convolutional neural network. They were classifying the lesions into either malignant or benign. They performed their experiments on HAM-10000 images (ISIC 2018, 2019, 2020), Their proposed model InSiNet was developed based on the inception module in GoogleNet. Their proposed model was based on four parts: stem inception module, Conv layer and classifier layer. They evaluated their proposed model based on accuracy score on ISIC 2018, 2019 and 2020 dataset. On dataset ISIC 2018, it was giving the accuracy score of 94.59%, 91.89% for ISIC 2019, and 90.54% accuracy on ISIC 2020 dataset. They compare the performance of their proposed model with GoogleNet, DenseNet20, EfficientNetB0, ResNet152V2, , RBF support vector machine, and random forest, logistic 23 regression. By comparing the performance of their proposed model with these models, their proposed model was giving the high accuracy score. [46] Proposed a method for skin cancer detection. First of all in their method, they applied noise removal and image enhancement techniques for improving the quality of images. After which they applied GLCM for feature extraction. Based on these extracted features, they trained SVM for classification. They classified into either cancerous or non-cancerous. They achieved an accurate score of 95%.

II. PROPOSED APPROACH

The results and performance of our work have been evaluated using various strategies. Figure 1 presents a flowchart outlining the proposed workflow

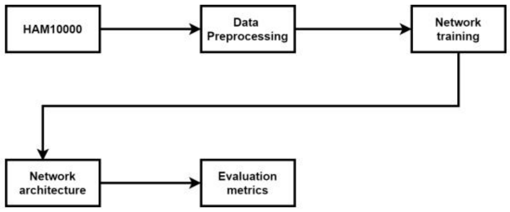

Figure 1: Flow Chart of Our Proposed Workflow

DATASET: We have used the HAM10000 2018 for our work. HAM10000 was created by Noel Codella. This dataset consists of a total of 10015 images of seven different types of dermatoscopic images. The seven classes (melanocytic nevi, melanoma, benign keratosis-like lesions, basal cell carcinoma, pyogenic granulomas, hemorrhage, actinic keratosis, intraepithelial carcinoma, dermatofibroma) from which this dataset is made up. The dataset has been widely used in computer-aided diagnosis and skin cancer classification research. It is freely available to the public and can be downloaded [50]. The following table 1 shows the distribution of these classes in the dataset.

Table 1: Distribution of classes in dataset.

Class	Number f samples
Melanocytic Nevi	6,670
Melanoma	1,319
Benign keratosis-like lesions	1,095
Basal cell carcinoma	514
Pyogenic granulomas an emorrhage	142
Actinic eratosis	327
carcinoma and Intraepithelial lermatofibroma	28

The below figure 2(a) and 1(b) shows the melanocytic nevi samples.

Figure 2: Sample Images of Melanocytic Nevi

The below figure 3(a) and 3(b) represent the benign keratosis-like lesions sample images.

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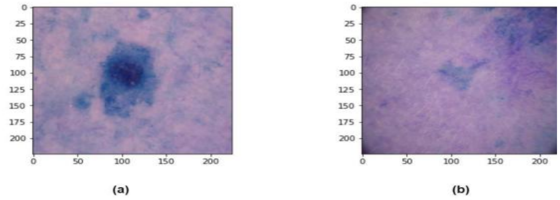

Figure 3: Sample images of Benign keratosis-like lesions

In figure 4(a) and 4(b), samples of melanoma are presented.

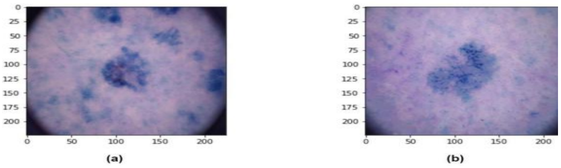

Figure 4: Samples images of Melanoma

Figure 5(a) and 5(b) denotes the Basal cell carcinoma sample images.

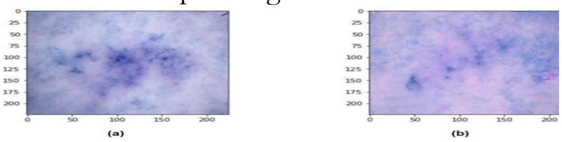

Figure 5: Sample images of Basal cell carcinoma

Figure 6(a) and 6(b) denotes the Pyogenic granulomas and hemorrhage sample images. While figure 7(a) and 7(b) denotes the actinic keratosis samples. Samples images of Intraepithelial carcinoma and dermatofibroma is presented in figure 8(a) and 8(b).

Figure 6: Sample images of Pyogenic granulomas and hemorrhage

Figure 7: Sample images of Actinic keratosis

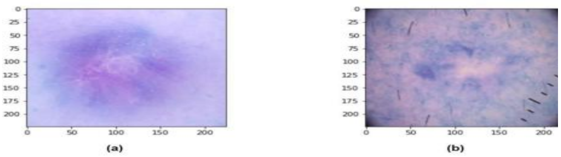

Figure 8: Intraepithelial carcinoma and dermatofibroma

For our work, we have used 60% of data for training, 20% for validation and 20% for testing as shown in table 2.

Table 2: Distribution of data for model training

Phase	Instances in perct.
Training	60
Validation	20
Testing	20

NETWORK TRAINING: For our problem, we have used an ensemble learning model. In which we have combined four different deep learning models namely InceptionV3, ResNet50, Xception and Efficient Net. We trained these classifiers manually also, as well as for ensemble learning. Ensemble learning is a method that involves combining multiple models to improve the predictive model's accuracy and generalization. Because of the high complexity of deep neural networks, which usually leads to overfitting or generalization errors, ensemble learning can be especially useful in deep learning for image classification. For training the model, we use the categorical cross entropy loss function. We trained each classifier up to 50 epochs, and used Adam as an optimizer.

PROPOSED ARCHITECTURE: In our proposed architecture as shown in figure 9, we have combined four popular deep learning CNN based architectures namely InceptionV3, EfficientNet, ResNet50 and Xception by the use of learning method known as (EL)Ensemble learning which involves training and merging multiple models to improve the overall performance of the method. Ensemble methods in deep learning can be used to improve model accuracy and robustness, especially when dealing with large and complex datasets. There are several approaches to implementing ensemble learning into deep learning. Among the most common approaches are bagging, boosting and stacking. The stacking method involves training various models and feeding their outputs into a final model that makes the final prediction. When individual models have different strengths and weaknesses, stacking can be useful. The following given

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figure 9 shows the overall methodology of the proposed work. In this work, we ensemble four CNN architectures utilized to classify the melanoma, which is followed by fully connected layers, in which the SoftMax function is used in the end for classification.

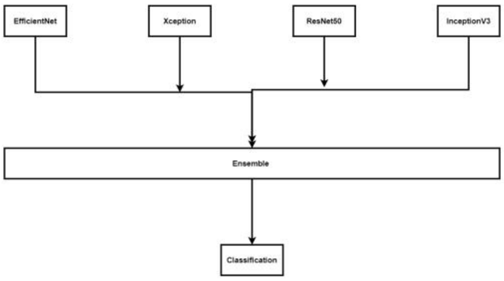

Figure 9: Combined our Proposed four popular deep learning CNN based architectures

In our work, we first resized our input images to size of 299x299 and 224x224. It is because,
InceptionV3 and Xception process images of size 299x299, and ResNet50 as well as Efficient Net processing images of dimensions 224x224.

Efficient Net: Efficient Net is a family of convolutional neural networks (CNNs) that were introduced in a [51]. Efficient Net's goal was to develop a family of CNNs that were more efficient and effective than existing architecture while also being easier to scale to different problem domains. To accomplish this, the authors created a novel compound scaling method that uniformly scales the depth, width, and resolution dimensions in a principled manner. EfficientNet models are made up of a stem, a series of blocks, and a head. The stem is a small collection of layers that preprocess the input image, whereas the blocks are repeated building blocks that include convolutional, activation, and normalization layers. The head is a collection of layers that generate the final output. The authors discovered that by carefully balancing the number of layers, layer width, and input image resolution, they could create models that were both more accurate and efficient than previous architectures. EfficientNet methods have attained state-of-the-art results on a variety of benchmark datasets while being significantly smaller and faster than other top-performing models. This makes them especially well-suited for use cases with limited computational resources or where speed is critical, such as mobile devices or real- time applications. The below figure 10 shows the diagram of Efficient Net.

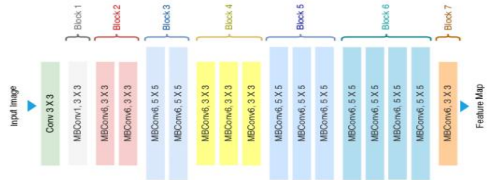

Figure 10: Efficient Net Diagram

Inception V3: InceptionV3 [52] is indeed a deep convolutional neural network (CNN) architecture introduced by Google researchers in 2015. It is a variant of a original Inception architecture, which was intended to enhance image classification computational efficiency and accuracy. InceptionV3 helps in extracting features from input images and categorizes them using a combination of convolutional based layers, pooling and FC layers. It also includes several key innovations, such as the use of factorized convolutions, which reduce the number of parameters and computation required by the model, and the use of batch normalization, which aids in the reduction of over fitting. The below figure 11 shows the diagram of Inception V3.

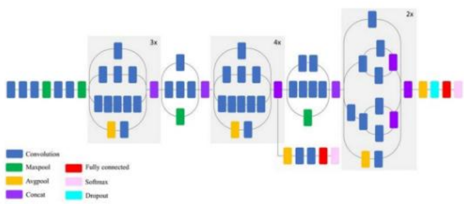

Figure 11: InceptionV3 flowchart diagram

The InceptionV3 model has the following specifications:

The input to the model is a 299x299x3 image.The model consists of 48 convolutional layers, 9 inception modules, 1 global average pooling layer, and 1 fully connected layer.

The output layer of the model is a SoftMax layer with 1,000 nodes, which represents the predicted probabilities for each of the 1,000 classes in the ImageNet

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dataset.

The over-all no. of parameters in this model is approximately 23 million. InceptionV3 was trained on the ImageNet dataset, which consists of over one million images and 1,000 object categories.

ResNet50: ResNet50 is a convolutional neural network (CNN) architecture that was introduced in [47,48]. It is a modification of the original ResNet architecture, which was created to address the issue of vanishing gradients in very deep neural networks.

ResNet50 implements residual connections, which allow the gradient to propagate more easily throughout the network, allowing for the training of much deeper networks. The residual connections enable the network to learn the identity function as well, which aids in the preservation of information from previous layers and reduces the risk of overfitting.

The key features of ResNet50 are:

The input to the model is a 224x224x3 image. The model consists of 50 convolutional layers, including a combination of 1x1, 3x3, and 1x3 convolutional filters. The output layer of the model is a SoftMax layer with 1,000 nodes, which represents the predicted probabilities for each of the 1,000 classes in the ImageNet dataset.

The aggregate no. of parameters in the model is approximately 25 million. ResNet50 was trained on the ImageNet dataset, which consists of over one million images and 1,000 object categories. In Figure 12 shows the ResNet50 Flow diagram.

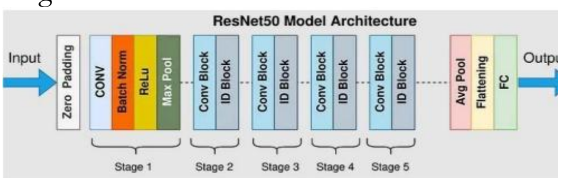

Figure 12:ResNet50 flowchart diagram

Xception: Google researchers introduced Xception, a deep convolutional neural network (CNN) architecture, in 2016. It is a variant of the Inception architecture, which was designed to improve image classification accuracy while reducing the model's parameter requirements.

To improve model efficiency, Xception implements depthwise separable convolutions, which divide traditional convolutional filters into separate depthwise and pointwise convolutional filters. The depthwise convolutional filters capture spatial dependencies in the input image, while the pointwise convolutional filters combine the output of the depth - wise separable convolutional filters to produce the final output. The key features of Xception model includes

The input to the model is a 299x299x3 image.

The model consists of 36 convolutional layers, including a combination of depth wise separable convolutions and 1x1 convolutions. The output layer of the model is a SoftMax layer with 1,000 nodes, which represents the predicted probabilities for each of the 1,000 classes in the ImageNet dataset.

The complete parameter in the model is approximately 22 million. Xception was trained on the ImageNet dataset, which consists of over one million images and 1,000 object categories. The below figure 13 denotes the Xception model diagram.

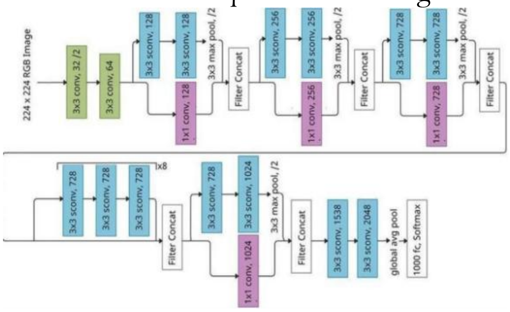

Figure 13: Xception model flow chart diagram

In our proposed model, we first pass the data to process by each of these base learners including InceptionV3, Efficient Net, ResNet50 and Xception. After processing by these models, the output is then combined and is processed by completely integrated layer for final classification using SoftMax activation function.

III. Results and discussions

This section focuses on the results of our proposed method with base models based on F1- score., precision, accuracy and recall.

1. ***Accuracy:*** Figure 14 shows the comparison of our proposed model with

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other models based on accuracy score.

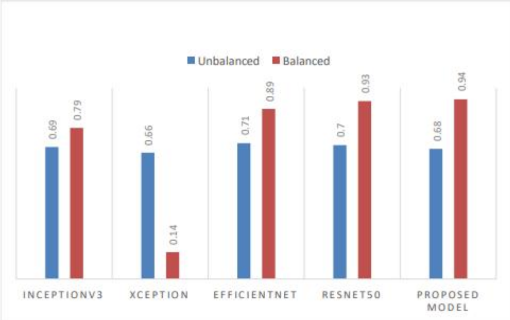

Figure 14: Comparison of models based on accuracy score

We trained these classifiers on unbalanced data, and we also train after balancing the data using random sampling. When the data was unbalanced, the efficient net was giving the high accuracy score of 0.71. Our proposed model gave an accuracy score of 0.68 on unbalanced data. But when we balanced the data, then our proposed model gave the highest accuracy score of 0.94. While the ResNet50 model was giving the second highest accuracy score of 0.93. But at the same time, Xception model was giving an accuracy score of 0.14 on balanced data but was giving an accuracy score of 0.66 on unbalanced data.

2. **Precision**: Figure 15 shows the comparison of our proposed model with other models based on precision scores trained in imbalanced and balanced data.

Figure 15: Precision score based comparison of models

When the data is imbalanced, our proposed model was giving high precision score of 0.42, while Xception model was performing worst in term of precision on unbalanced data. Inception V3 model was giving a precision score of 0.3 for unbalanced data. But when we balanced the data, then our proposed model and ResNet50 was giving the highest precision score of 0.93. At the same time, Xception model was again giving the lowest precision score of 0.14 for balanced data as well also. The precision of efficient net was also improved from 0.38 to 0.89 by balancing the data.

3. Recall: The figure 16 below shows the comparison based on the recall score of our proposed model in comparison with other models.

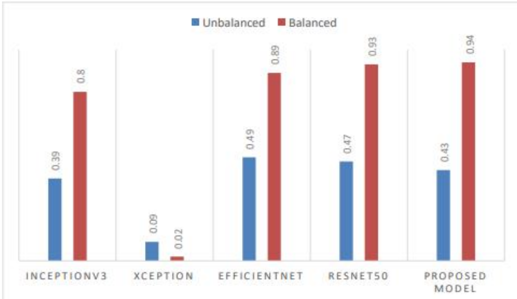

Figure 16: Recall score-based comparison of models

The above figure 16 shows the comparison based on recall score of our proposed model in comparison with other models. On unbalanced data, Efficient net was giving a high recall score of 0.49, ResNet50 was giving the recall score of 0.47. Inception V3 gave a recall score of 0.39, but our proposed model gave the recall score of 0.43 on unbalanced data. But when we balanced the data, then our proposed model was giving the highest recall score of 0.94. At the same time, on balanced data ResNet50 was giving the second highest recall scores of 0.93 on balanced data. But the Xception model was giving the lowest recall score of 0.02 on balanced data as well lowest recall score of 0.09 for balanced data as well. Efficient net was giving a recall score of 0.89 for balanced data.

4. F1-score: Figure 17, shows the F1-score of our proposed model in comparison with other models trained on unbalanced data as well as on balanced data.

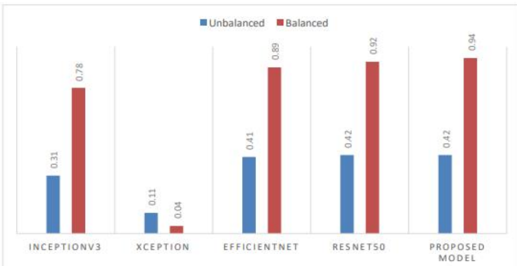

Figure 17: Comparison of models based on F1-score

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The above figure 17 shows the F1-score of our proposed model in comparison with other models trained on unbalanced data as well as on balanced data. When the data was unbalanced, then our proposed model and ResNet50 was giving the high F1-score of 0.42, Efficient Net was giving F1-score of 0.41. But Xception was giving the lowest F1-score of 0.11 for unbalanced data. But when we balanced the data, then our proposed model was giving the highest F1-score of 0.94. ResNet50 was giving the second highest recall score of 0.92, and Efficient Net was giving the recall score of 0.89. But again, here Xception model was giving the lowest F1 score of 0.04 on balanced data.

IV. Result Conclusion

Skin cancer is a serious and deadly disease that can be avoided by using sunscreen and performing regular skin checks. Early detection and treatment are critical for a positive outcome. Deep learning, a division of AI, has shown promise in detecting melanoma via medical image analysis, such as dermoscopy and clinical photography. Deep learning models have been created and trained on large datasets of images in recent years to accurately differentiate between benign and cancerous skin lesions. These models have demonstrated high sensitivity and accuracy in detecting melanoma, frequently outperforming human dermatologists. While still in the early stages, the use of deep learning in melanoma detection has-the capacity to increase precision and speed of diagnosis, leading to earlier detection and treatment of melanoma and, ultimately, better patient outcomes. In the current work, we use HAM10000 dataset for detection of skin cancer. In this dataset, there were seven different classes of skin cancer diseases images. We proposed a model based on ensemble learning, in which we have combined InceptionV3, EfficientNet, ResNet50 and Xception models. We are passing images through these models, then by using ensemble learning it is combined and classified using full layer connectivity and SoftMax activation. We tested the performance of these base models as well for comparison. Initially, when the dataset was unbalanced, then our proposed model results was not excellent. But after balancing the dataset, our proposed model was performing better in terms of accuracy, precision, recall and F1- score as compared to these base models. On balanced dataset, our proposed model was given an accuracy score of 0.94, precision value of 0.93 and 0.94 for recall and F1-score. On unbalanced dataset, the proposed mode was giving 0.68 value for accuracy, 0.42 for precision, 0.43 for recall and F1score was 0.42.

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