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Skin Cancer Classification using Multiple Convolutional Neural Networks

Praveen Raj A[1], Kanishk V[2], Vineesh K[3], A Senthilselvi[4]

[1,2,3]UG Student, Dept of Computer Science and Engineering with specialization in Artificial Intelligence and Machine Learning, SRM Institute of Science & Technology, Ramapuram, Chennai, India.

[4]Professor, Dept of Computer Science and Engineering, SRM Institute of Science & Technology, Ramapuram, Chennai, India

E-mail: [1]pa3283@srmist.edu.in, [2]kv7462@srmist.edu.in, [3]kp5530@srmist.edu.in, [4]senthila3@srmist.edu.in

Abstract

Skin cancer is a significant threat to the global health, with over 2.1 million new cases diagnosed annually worldwide. Timely detection and treatment are vital for improving survival rates, yet the limited availability of dermatologists in remote regions poses a significant barrier. The utilization of Artificial Intelligence (AI) and Deep Learning (DL) has seen a remarkable surge in recent years for skin cancer prediction. This study conducts an in-depth review of advanced skin cancer prediction methods employing deep learning techniques and explores the diverse array of machine learning algorithms applied in this context. Skin cancer comprises seven distinct diagnoses, presenting a formidable challenge for dermatologists due to the overlapping phenotypic traits. Conventional diagnostic accuracy typically ranges from 62% to 80%, underscoring the potential of machine learning to enhance diagnosis and treatment. While some researchers have created binary skin cancer classification models, extending this to multiple classes with superior performance has been elusive. A deep learning classification model for various skin cancer types, yielding promising results that highlight the superiority of deep learning in classification tasks is developed. The experimental outcomes demonstrate that the individual accuracy of Sequential, ResNet50, DenseNet201, VGG-16 and EfficientNetB0 models are aggregated and yields the maximum occurring output value from all the models.

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Furthermore, a comparative analysis with the latest skin classification models underscores the superior performance of the proposed multi-type skin cancer classification model.

Keywords: HAM10000, Sequential, ResNet50, DenseNet201, VGG16 EfficientNetB0

1. Introduction

Skin cancer stands as a pervasive global malignancy, with its incidence steadily surging in recent decades. Timely and precise identification and classification of skin lesions in their early stages constitute paramount importance in ensuring effective treatment and ultimately enhancing patient outcomes. Leveraging advanced machine learning and deep learning algorithms, the model possesses the capability to classify skin cancer across its various types. In order to advance the field of skin cancer diagnosis and treatment, the model is made to distinguish and classify skin malignancies into seven distinct classes: Dermatofibroma, Melanocytic Nevi, Melanoma, Benign Keratosis-Like Lesions, Basal Cell Carcinoma, Actinic Keratoses and Intraepithelial carcinoma, Dermatofibroma, Pyogenic Granulomas, and Haemorrhage. The most common skin growth is the melanocytic nevi also known as moles are benign growths of melanocytes which are referred as pigment-producing cells in the skins. Majority of the moles are harmless but there could be some which develops into a cancer. It is mostly found it skin areas which are exposed to sun like face, neck and hands. Melanoma cancer is one of the deadliest skin cancers of all. Early detection could significantly improve the survival rate. Benign keratosis-like lesions are non-cancerous skin growths resulting from prolonged sun exposure. They surround conditions like actinic keratoses, seborrheic keratoses, and solar lentigines. These growths originate in the basal cells, the foundation of the outermost skin layer, the epidermis. Among them, basal cell carcinoma, although slow-growing, seldom metastasizes to other body parts. Actinic keratosis, on the other hand, is a sun-induced precancerous growth, often presenting as a scaly, red patch on the skin, treatable with methods like cryotherapy, topical medications, or laser therapy. Intraepithelial carcinoma is a form of skin cancer originating in the external layer of the skin, known as the epidermis. Importantly, it has not yet invaded deeper skin layers or other body regions. Effective treatments for intraepithelial carcinoma include cryotherapy, topical medications, and laser therapy. Dermatofibroma, conversely, is a harmless skin growth often mistaken for a mole or a wart. It is generally small, round, and with varying degrees of firmness, dermatofibromas do not pose any health risks and typically do not require any medical treatment. Pyogenic granulomas are benign, red, raised skin growths prone to bleeding, treatable with cryotherapy, medications, or lasers. Diagnosis often involves an eye examination and, sometimes, a biopsy, though this can be time-consuming and open to interpretation.

2. Related Works

The literature on skin cancer classification and detection through deep learning techniques has experienced significant expansion in recent years. Researchers have explored diverse approaches to enhance efficiency and accuracy of diagnosing the skin cancer. A notable study by Kausar et al. [1] specifically focused on multiclass skin cancer classification, employing an ensemble deep learning models that were finely tuned. The authors provided examples of the method's efficacy in producing precise classification outcomes. Thomas et al. [2] made a contribution to the subject by creating interpretable deep learning systems for the multi-class segmentation and classification of skin cancer that is not melanoma. Their work aimed to introduce transparency into the decision-making process of deep learning models, a crucial factor for fostering acceptance and trust in such systems, particularly in medical applications.

The ISIC (International Skin Imaging Collaboration) dataset, highlighted in Codella et al. [3], has been instrumental in advancing skin cancer research, serving as a benchmark for developing and evaluating detection algorithms. Albawi et al. [4] introduced a dermatologist-level deep learning model for skin cancer classification, showcasing the potential of these models to rival human experts in diagnosis. Vijayalakshmi [5] focused on melanoma detection using image processing and machine learning, emphasizing the synergy of these techniques for improved accuracy. Datta et al. [6] innovatively incorporated soft attention mechanisms to boost skin cancer classification performance, yielding promising results in capturing relevant features. Manne et al. [7] did a thorough review on the potential and pitfalls of employing Convolutional Neural Networks (CNNs) for classifying skin cancer. They provided valuable insights into where things stand now, the hurdles we're facing, and the possible paths forward. Duggani and Nath [8] provided a technical review on deep learning approaches for skin cancer detection and segmentation, summarizing advancements and highlighting existing methodologies' strengths and limitations. Wu et al. [9] conducted a comprehensive review on skin cancer classification with deep learning, covering various architectures and methodologies.

Lastly, Ashraf et al. [10] developed a framework for skin cancer detection with the assistance of transfer learning, emphasising the use of region-of-interest-based techniques to improve the performance of deep learning models in locating skin cancer regions. Various studies, such as Dong et al. [11], Shehzad et al. [12], Kumar et al. [13], and Lau and Al-Jumaily [14], have delved into diverse facets of skin cancer detection, encompassing segmentation, ensemble learning, and early detection through neural networks. A noteworthy accomplishment was made by Esteva et al. [15], who demonstrated how deep neural networks may match human diagnostic expertise by classifying skin cancer at the dermatologist level. Khan et al. [16] projected a unified framework for skin lesion segmentation and classification, merging and selecting features from different neural network architectures to enhance overall diagnostic accuracy. In a comprehensive review, Dildar et al. [17] highlighted the application of deep learning techniques in skin cancer detection, covering aspects like convolutional neural networks and providing an overview of the current research landscape. Polat and Koc [18] focused on applying convolutional neural networks and one-versus-all classification in tandem to identify skin conditions from dermoscopy images. Their integrated deep learning framework aimed to address the challenges associated with identifying various skin diseases.

The literature survey provides a comprehensive view of the varied approaches and methodologies employed by researchers in advancing the field of skin cancer detection through deep learning techniques. The studies discussed contribute valuable insights, covering aspects ranging from dataset utilization to model interpretability. This collective body of research enhances the understanding of the current state and future prospects in this crucial domain of medical imaging research.

3. Problem Statement

The challenge of skin cancer classification revolves around crafting a sophisticated and precise system to categorize dermatological images based on the presence of skin lesions. The primary objective is to construct machine learning or deep learning models adept at distinguishing between various types of skin cancers, encompassing melanoma, basal cell carcinoma, and other lesions of both malignant and benign nature. The overarching purpose of this classification system is to stand as a valuable asset in dermatology, providing essential support to healthcare professionals, particularly dermatologists, in the timely detection and diagnosis of skin cancers.

Central to this challenge is a dataset comprising images that portray a wide array of skin lesions. These images encapsulate the intricacies and variations inherent in diverse skin conditions, presenting a formidable task for classification models to generalize patterns and make accurate predictions across a spectrum of cases. The inherent complexity of skin images necessitates the application of advanced computational techniques, involving both machine learning and deep learning, to adeptly capture and interpret relevant features indicative of different skin cancer types.

A pivotal consideration in addressing this challenge is the management of imbalances within the dataset. The uneven distribution of various skin cancer types can potentially introduce bias into the model's learning process, resulting in skewed classifications. Consequently, achieving a balanced and representative dataset emerges as a critical factor in developing a robust skin cancer classification system. Moreover, the success of the classification system hinges on its capacity to achieve a high level of sensitivity and specificity. Sensitivity ensures the accurate identification of true positive cases, while specificity guarantees precise classification of true negatives. Striking an optimal balance between these metrics is crucial to minimizing both false positives and false negatives, thereby enhancing the reliability and clinical utility of the skin cancer classification system.

In summary, the skin cancer classification challenge involves harnessing advanced computational methods to design models proficient in accurately categorizing diverse skin lesions. The intricacies of the dataset, the need for balance, and the pursuit of high sensitivity and specificity introduce layers of complexity to the task, underscoring the significance of developing a robust and clinically valuable solution for the early detection and diagnosis of skin cancers.

4. Proposed Work

The proposed method is that we have developed a Sequential model and four pre-trained deep learning-based models of ResNet50, DenseNet201, VGG-16 and EfficientNetB0 with the HAM10000 dataset [3]. The Sequential model and four distinct pre-trained models have been chosen to efficiently acquire both the diagnostic and textural difference present in skin cancer images that are converted to an array with a 32x32 pixel resolution and separating the RGB colour channels individually saving them in a csv file involves breaking down the image into its constituent components for further processing or analysis.

To address the imbalanced distribution of images across classes in the dataset, RandomOverSampler from the imbalanced-learn library is implemented. This preprocessing technique resulted in a balanced dataset comprising 46,935 images, with 70% allocated for training which is 32854 images and 30% for testing which is 14081 images. At the second stage, the outputs are obtained by aggregating the maximum occurrence value output from all the models to classify the seven classes of skin cancer. Data manipulation and preprocessing tasks, along with the conversion of images to NumPy arrays, were accomplished through the use of Pandas and NumPy. The versatile capabilities of Pandas facilitated effective manipulation of tabular data, while NumPy played a crucial role in converting images into arrays suitable for further processing. The image classification process was carried out using OpenCV, a robust computer vision library known for its diverse image processing functionalities. The construction and training of the models were undertaken using TensorFlow and Keras. Leveraging the high-level abstractions of Keras atop TensorFlow provided a seamless and efficient framework for building and training deep learning models. A Sequential model and four pre-trained deep learning-based models of ResNet50, DenseNet201, VGG-19 and EfficientNetB0 is built and trained individually. This combination allowed for the implementation of sophisticated neural network architectures tailored to the task of skin cancer classification.

To visualize and graphically represent the training process, including loss and accuracy metrics, Matplotlib and Seaborn were employed. These visualization libraries offered a comprehensive set of tools for creating informative plots and charts, aiding in the interpretation and assessment of the model's performance during training. The seamless integration of these tools facilitated a holistic approach to the development and evaluation of skin cancer classification models. The outputs have been obtained by aggregating the maximum occurring output from all the models to classify the seven classes of skin cancer. Figure 1 represents the flow chart of the proposed model.

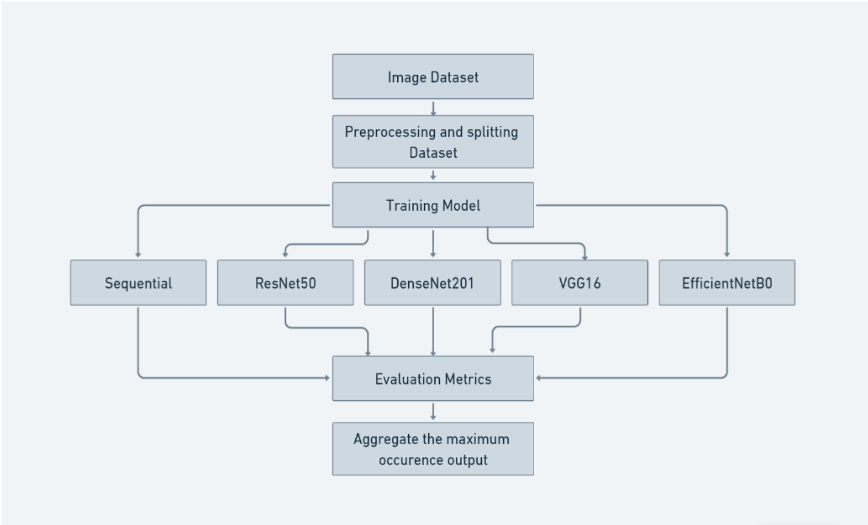

Figure 1. Block Diagram of Training Models

4.1 Dataset Description

HAM10000 [3] stands as a publicly accessible repository housing an extensive assortment of dermatoscopic imagery capturing pigmented skin lesions, thus serving as a pivotal resource within the domains of dermatology and machine learning. There is a total of 10,015 images in this collection, and they are very important for efforts related to skin cancer classification and lesion detection.

The dataset was created by the “Department of Dermatology at the Medical University of Vienna” and includes images from multiple sources, including clinical settings and dermatology clinics. The images in the dataset are high-resolution and typically capture skin lesions in detail. They are classified into seven different diagnostic categories, which include basal cell carcinoma, melanocytic nevi, melanoma, squamous cell carcinoma, actinic keratoses, benign keratosis-like lesions, and vascular lesions. Figure 2 displays sample images from the HAM 10000 dataset, while Figure 3 illustrates the distribution of categories within the dataset.

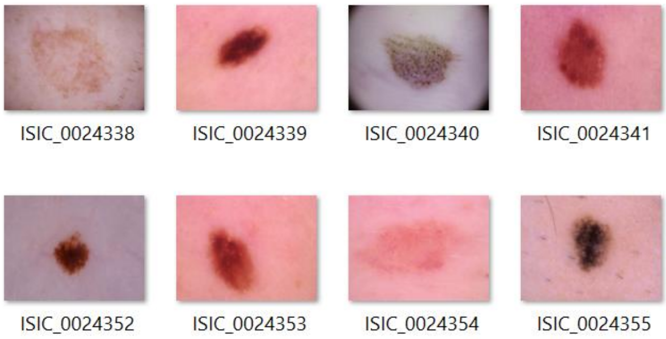

Figure 2. Sample Images for HAM10000 Images

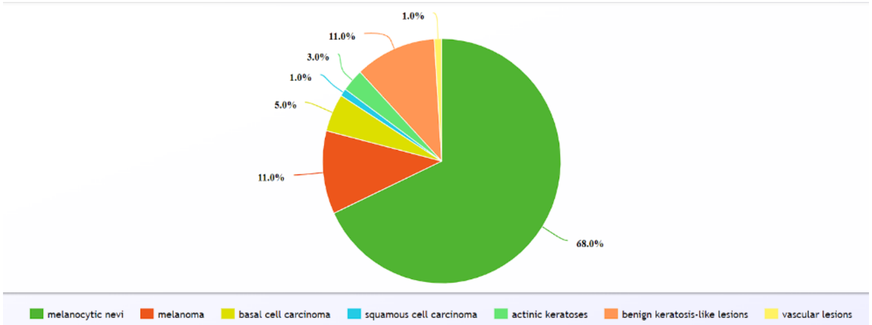

Figure 3. Category Distribution of HAM10000 Dataset

4.2 Convolutional Neural Network Models

4.2.1 Sequential

A Sequential model is a neural network architecture characterized by its linear layer stacking, wherein data moves sequentially, starting from input layer which ultimately leads to the output layer. These models are straightforward in structure and find application in tasks such as specific convolutional neural networks (CNNs). The architecture is systematically organized, leveraging a series of convolutional blocks, max-pooling layers, batch normalization, and fully connected layers to effectively extract hierarchical features from input images and make predictions across multiple classes.

The input layer is configured to receive images with a dimension of [32, 32, 3], denoting a spatial resolution of 32x32 pixels and three-color channels (RGB). Subsequently, two convolutional blocks are employed, each consisting of two consecutive convolutional layers. The initial convolutional layer in each block comprises 32, 64, 128, and 256 filters, respectively, utilizing a 3x3 filter size, Rectified Linear Unit (ReLU) activation function, and 'same' padding to maintain spatial dimensions. In order to decrease computational complexity and downsample the feature maps, a MaxPooling2D layer is added after every pair of convolutional layers. After each max-pooling and convolutional layer, batch normalisation layers are systematically added. Through the normalisation of network activations, these layers help to stabilise and speed up the training process. Then, to make the switch to fully connected layers easier, a Flatten layer is used to convert the 3D tensor output from the convolutional layers into a 1D tensor.

To mitigate overfitting, a Dropout layer with a dropout rate of 0.2 is incorporated after the flattening step. Three fully connected dense layers ensue, comprising 256, 128, and 64 units, each activated by a Rectified Linear Unit (ReLU) function. Batch normalization layers follow each dense layer, contributing to the stability of the network during training. The fourth dense layer, consisting of 32 units, introduces L1L2 regularization to penalize large weights, thereby enhancing the model's robustness and generalization capabilities.

The final layer of the model is a Dense layer with 7 units, aligning with the number of distinct classes in the skin cancer classification task. This layer employs a softmax activation function, producing a probability distribution across the various classes. Afterward, the model undergoes compilation employing categorical crossentropy as the loss function, the Adam optimizer set at a learning rate of 0.001, and accuracy as the evaluation metric. This setup prepares the model for training on the skin cancer dataset, enhancing its ability to precisely categorize skin cancer images by leveraging patterns acquired from the extensive 'imagenet' dataset.

4.2.2 ResNet50

ResNet-50 is a convolutional neural network comprising 50 layers, which is renowned for its effectiveness in image recognition. It is ingenious feature is the concatenation of residual blocks, including skip connections to deal with the vanishing gradient problem and organize the training of deep networks. The ResNet50 model is set up with pre-trained weights from the 'imagenet' dataset, and it's set to skip the fully connected layer at the top.

The input shape is set to (32, 32, 3), indicating that the model expects images with a spatial resolution of 32x32 pixels and three-color channels (RGB). The choice of ResNet50 for this skin cancer classification task brings its architecture, known for its deep residual learning, to the forefront. After the ResNet50 base, the model's output goes through a GlobalAveragePooling2D layer, crunching the average values for each feature map and shrinking the spatial dimensions. Then, a Dense layer steps in with 512 units and a ReLU activation function, acting like a fully connected layer to dig deeper into the intricate patterns in the data.

4.2.3 DenseNet201

DenseNet-201 is a highly regarded convolutional neural network structure, known for its effectiveness in image classification tasks. Its notable feature is its dense interconnection scheme, which establishes direct connections between each layer and all subsequent layers. This approach promotes the reutilization of features and improves the flow of gradients within the network. The DenseNet201 model is set up with pre-trained weights from the 'imagenet' dataset, and it's set to skip the fully connected layer at the top. The input shape is set to (32, 32, 3), indicating that the model expects images with a spatial resolution of 32x32 pixels and three-color channels (RGB).

The output of the model is passed through a GlobalAveragePooling2D layer, which computes the average value for each feature map, effectively reducing the spatial dimensions. This is followed by a Dense layer with 256 units and a ReLU activation function, serving as a fully connected layer to further capture complex patterns in the data.

4.2.4 VGG16

VGG16 is a popular convolutional neural network with a clean and impactful design. It hails from the Visual Geometry Group at Oxford University and boasts a total of 16 layers. Its core features include layers of 3x3 convolutions mixed with max-pooling. The model comes pre-loaded with weights from the 'imagenet' dataset and is set up to skip the top fully connected layer. It's configured to handle input images at a resolution of 32x32 pixels with three RGB color channels.

By calculating the average value for every feature map, a GlobalAveragePooling2D layer reduces the spatial dimensions of the model's output. The Dense layer, which has 128 units and a ReLU activation function, comes next. It functions as a fully connected layer to help identify more intricate patterns in the input.

4.2.5 EfficientNetB0

EfficientNetB0 represents a convolutional neural network design specifically tailored for computer vision tasks, distinguished for its systematic approach to scaling, which optimizes the model's size, computational requirements, and accuracy. The EfficientNetB0 model is set up with pre-trained weights from the 'imagenet' dataset, and it's set to skip the fully connected layer at the top. The input shape is set to (32, 32, 3), indicating that the model expects images with a spatial resolution of 32x32 pixels and three-color channels (RGB).

Following the base EfficientNetB0 model, the output is processed through a GlobalAveragePooling2D layer. This layer computes the average value for each feature map, effectively reducing the spatial dimensions. Subsequently, a Dense layer with 128 units and a Rectified Linear Unit (ReLU) activation function is introduced. This layer serves as a fully connected layer to capture intricate patterns in the data, enabling the model to discern complex relationships.

The final layer of all the models of CNN is another Dense layer, configured with 7 units and a softmax activation function. This layer produces a probability distribution across the 7 classes of skin cancer. Each unit in the output corresponds to a specific class, and the softmax activation ensures that the model's output represents valid class probabilities. For fine-tuning and transfer learning, the code iterates through all layers in the original EfficientNetB0 ResNet50, DenseNet201, VGG16, model, setting their trainable attribute to False. This step ensures that the pre-trained weights remain fixed and are not updated during subsequent training on the skin cancer dataset. By preserving the knowledge gained from the 'imagenet' dataset, the model can adapt its features to the specific characteristics of skin cancer images.

Finally, all the models undergo compilation employing categorical cross entropy as the loss function, the Adam optimizer set at a learning rate of 0.001, and accuracy as the evaluation metric. This setup prepares the model for training on the skin cancer dataset, enhancing its ability to precisely classify skin cancer images by leveraging patterns acquired from the extensive 'imagenet' dataset.

4.3 Ensemble Classification Aggregation Strategy

The approach involves obtaining predictions from five different models using the model.predict() function, extracting the class values with np.argmax(), and then aggregating these class values into an array. To determine the most frequently occurring class, the np.bincount() function is employed on this array, allowing the identification of the class with the highest occurrence among the model predictions.

This approach significantly bolsters robustness by mitigating the influence of individual model errors, amplifying the model's capacity for generalization. The synergy among diverse models, each adept at capturing distinct facets of underlying data patterns, fosters heightened accuracy compared to standalone models. However, the utilization of frequency-derived outputs may introduce added intricacy to the model, particularly in the orchestration of predictions from multiple sources.

5. Results and Discussion

The success of the proposed models was assessed by measuring their ability to produce accuracy and loss of training and test dataset. The accuracy of individual models of Sequential, ResNet50, DenseNet201, VGG-16 and EfficientNetB0 is 98.33%, 98.46%, 94.19%, 97.39% and 76.27% respectively.

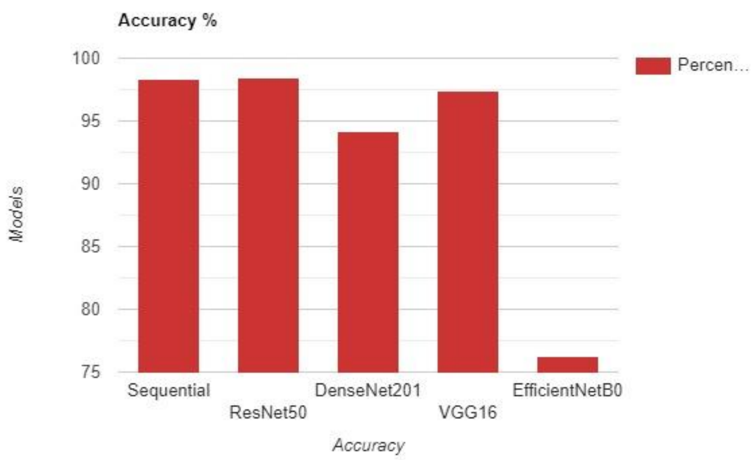

Figure 4. Accuracy Comparison of Individual Models

Figure 4 represents the test accuracy of individual models. Figure 5 to Figure 9 represents the Training and Test individual deep learning models having different accuracy scores. Figure 10 to Figure 14 represents the confusion matrices that are useful for evaluating the performance of individual models.

5.1 Loss and Accuracy Graph of Training Vs Test Data

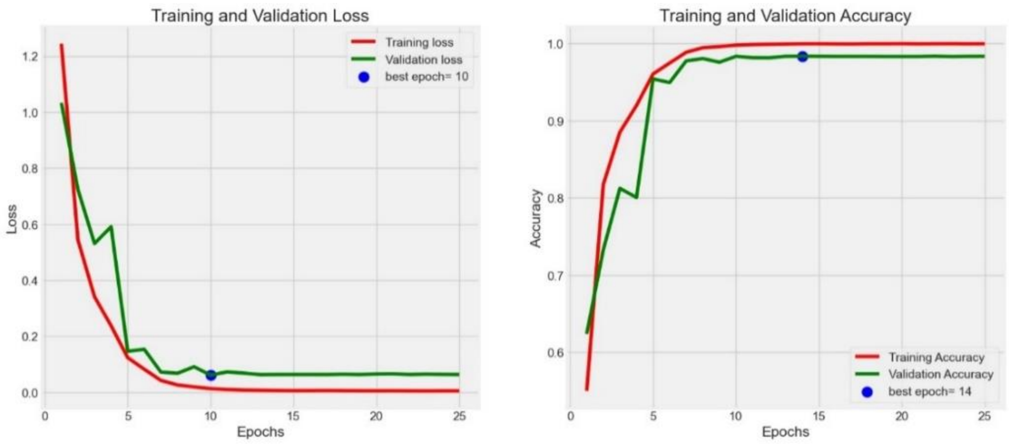

Figure 5. Accuracy vs Loss in Training and Validation of Sequential Model

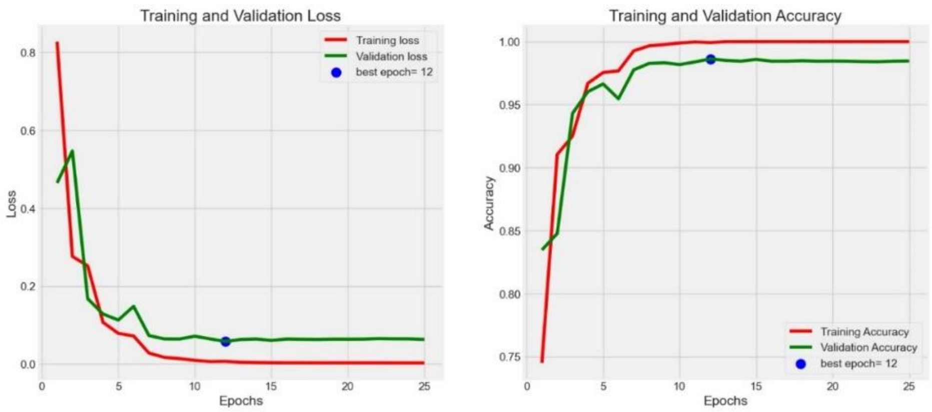

Figure 6. Accuracy vs Loss in Training and Validation of ResNet50 Model

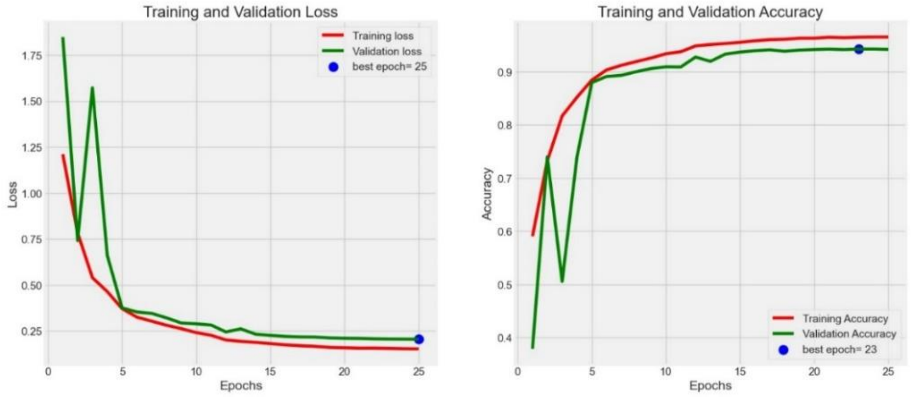

Figure 7. Accuracy vs Loss in Training and Validation of DenseNet201 Model

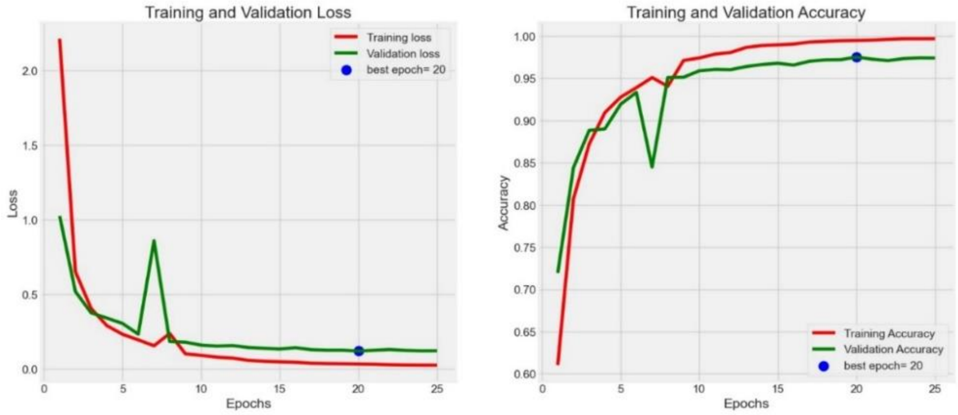

Figure 8. Accuracy vs Loss in Training and Validation of VGG16 Model

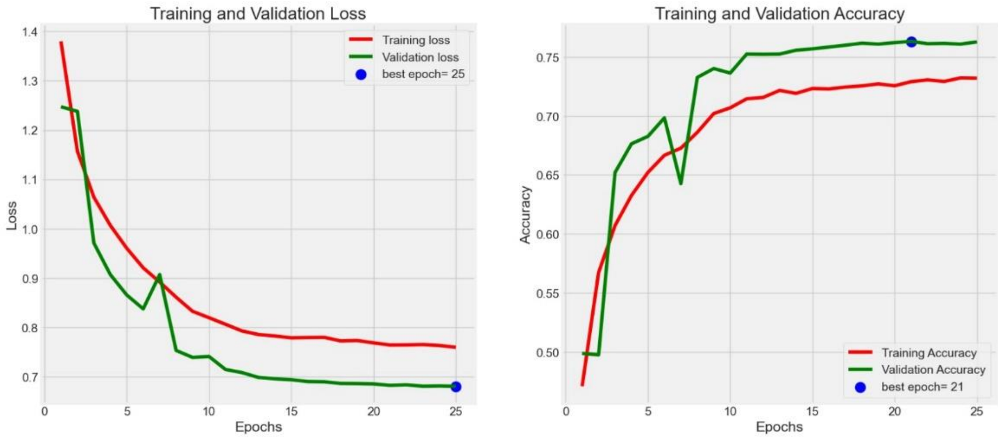

Figure 9. Accuracy vs Loss in Training and Validation of EfficientNetB0 Model

Overall, the declining validation and training loss specifies that the models are successfully fitting the training data and are capable to generalize to hidden data, a key aspect in avoiding overfitting. The increasing training accuracy further corroborates the model's improvement in predicting the correct labels for the training data. This improvement in accuracy is directly related to enhanced classification performance. In the same way, the model's improving ability to accurately classify unknown data is confirmed by the increasing validation accuracy. This conclusion is supported by the training and validation accuracy increasing, the training and validation loss decreasing, and the timing of the validation accuracy peak.

5.2 Confusion Matrix

The following confusion matrix summarizes the performance of a classification models with seven labels. It represents the number of correctly and incorrectly classified instances for each label. The diagonal elements indicate the correctly classified instances, while the off-diagonal elements represent the incorrectly classified instances. The row index corresponds to the true label, and the column index corresponds to the predicted label. Across all models, Label A consistently exhibits an average of 94 misclassifications, while the frequency of misclassifications decreases for subsequent labels. This trend underscores the high accuracy consistently demonstrated by the models, especially in distinguishing between the other labels where misclassifications are notably reduced. In summary, the confusion matrix provides valuable insights into the strengths and weaknesses of the classification model. By identifying areas for improvement, we can enhance its accuracy and applicability in real-world scenarios.

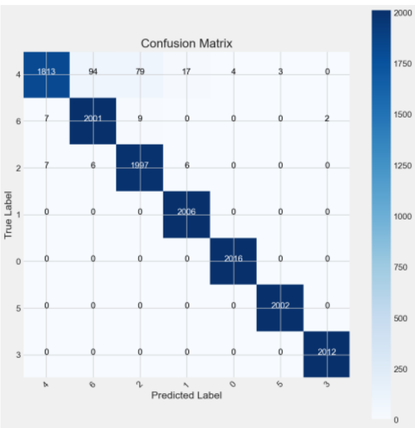

Figure 10. Sequential Model

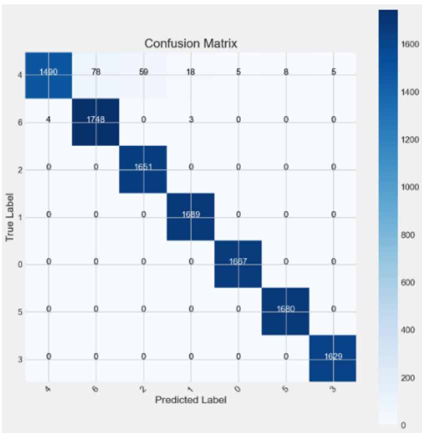

Figure 11. ResNet50 Model

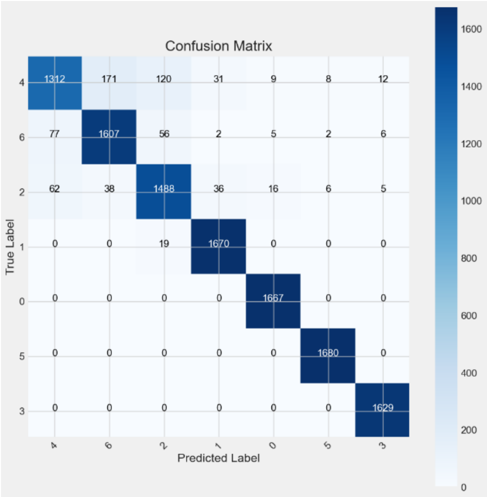

Figure 12. DenseNet201 Model

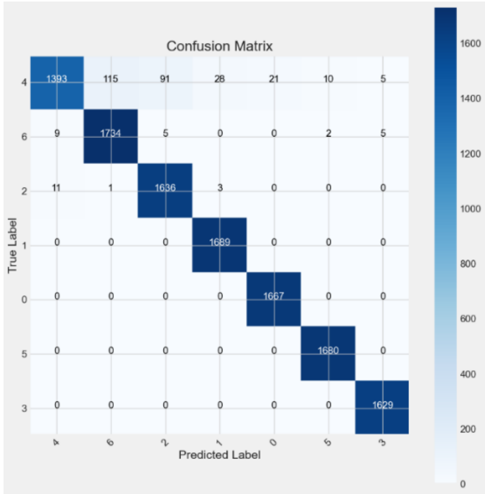

Figure 13. VGG16 Model

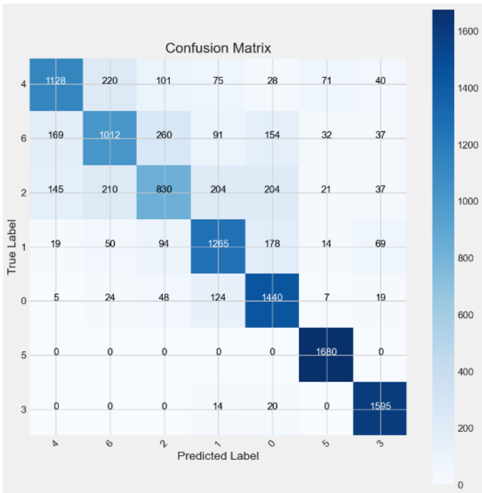

Figure 14. EfficientNetB0 Model

6. Conclusion

In-depth exploration and exhaustive investigations have been meticulously undertaken in the realm of skin cancer classification, yet most studies have not tackled the challenge of multiclass classification with exceptional performance. This model combines diverse pre-trained models, each with distinct properties, to efficiently acquire both the diagnostic and textural difference in skin cancer images by aggregating and yields the maximum occurring output value from all the models. Results demonstrate that the model outperforms recent deep learning methods in multiclass skin cancer classification, achieving an impressive highest accuracy of 98.46%. This underscores the budding of convolutional neural networks for skin cancer classification while emphasizing the approach ability to enhance classifier accuracy beyond individual models and surpass recent deep learning techniques in this domain.

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Author biography

Praveen Raj A is an Undergraduate Engineering Student in the Department of Computer Science Engineering with specialization in Artificial Intelligence & Machine Learning at SRM Institute of Science and Technology, Chennai, India. He completed his HSE schooling at S.B.O.A Matriculation & Higher Secondary School and SSLC at SBOA School and Junior College.

Kanishk V is an Undergraduate Engineering Student in the Department of Computer Science Engineering with specialization in Artificial Intelligence & Machine Learning at SRM Institute of Science and Technology, Chennai, India. He completed his HSE and SSLC schooling at G.T.A Vidhya Mandir.

Vineesh K is an Undergraduate Engineering Student in the Department of Computer Science Engineering with specialization in Artificial Intelligence & Machine Learning at SRM Institute of Science and Technology, Chennai, India. He completed his HSE and SSLC schooling at Shraddha Children's Academy.

Dr. A. Senthilselvi is an Professor in the Department of CSE at SRM Institute of Science and Technology, Chennai, India. She received her B.E degree in Electronics and Communication Engineering from Anna University, Tamilnadu, India, in 2005. She has received her M.Tech degree in Information Technology from Kalasalingam University, Tamilnadu, India, in 2010. She has completed her PhD degree in 2019 at Anna University, India.