An Efficient Skin Cancer Stage Diagnostic Approach Using Customized Inception V3 Deep Learning Model

Adnan Afroz[1], Shaheena Noor[2], Muhammad Umar Khan[3],
Shakil Ahmed Bashir[4], Jahangir Ahsan[5], Razia Maroof[6], Shoaib Mughal[7],Umair Jilani[8]
Dept. of Computer Engineering, Sir Syed University of Engineering and Technology, Karachi, Pakistan[1, 2, 5]
Dept. of Telecommunication Engineering, Sir Syed University of Engineering and Technology, Karachi, Pakistan[3, 8]
Dept. of Computer Science, FAST National University, Karachi, Pakistan[4]
Dept. of Electronic Engineering, Iqra University, Karachi, Pakistan[6]
Dept. of Computer Engineering, Bahria University, Karachi, Pakistan[7]

***Abstract*—Among all stages of skin cancer, Melanoma, Basel Cell Carcinoma (BCC), and Squamous Cell Carcinoma (SCC) have a significant impact on world health. Although deep learning offers promising potential for dermatological categorization, only limited disease groups have benefited, since most studies focus on particular illnesses rather than covering comprehensive human skin problems. Computerized analysis has been used in the past to identify cancer in skin lesion images, but challenges still persist mainly due to the multiple forms, textures, and sizes of lesions that complicate skin cancer classification. This research paper presents a Convolutional Neural Network (CNN) model customized to meet our requirements by using a pre trained InceptionV3 model along with Bayesian hyperparameter tuning. Using the ISIC 2024 and HAM 10000 datasets, the main objective is to classify skin lesions and differentiate between malignant Melanoma, BCC, and SCC. By implementing this customized model, the issue caused by variations in lesion appearance is effectively addressed, leading to more accurate predictions. Using Bayesian hyperparameter tuning can increase identification while decreasing computational cost. The proposed model performed strongly on the combined datasets by achieving combined average accuracy of 95.1 %, a precision of 94.42 %, a sensitivity of 97.3 %, a specificity of 98.8 %, and an F1 score of 95.7 %. These results demonstrate that the model significantly outperformed existing techniques and provided more accurate and consistent diagnosis of pigmented skin lesions compared to current standards.**

Keywords*—Melanoma; Basal Cell Carcinoma (BCC); Squamous Cell Carcinoma (SCC); Inceptionv3; Bayesian tuning; skin cancer classification

I. Introduction

Skin illnesses may be caused by hormones (e.g., acne) or by environmental factors such as pollution and sunlight. Most individuals ignore skin disorders and never go to the doctor. Skin illnesses account for 1.79% of all health-related ailments globally [1].

Melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma are main types of malignant skin tumors shown in Fig. 1. with a bad prognosis, and the number of cases growing, particularly in Europe and the United States. Among these three types of skin cancer, Melanoma is considered as the worst. Early identification of these classes is crucial since melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma may be almost entirely treated if caught early [2-4]. However, melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma continue to be diagnosed based on clinicians' subjective assessments. As a result, a very precise and quantitative diagnostic index is necessary. The categorization of these malignant skin lesions via dermoscopy methods has emerged as a crucial topic in dermatology and skin oncology in recent years [5, 6]. According to the Australian Institute of Health and Welfare, the average skin tumor change rate during the past 25 years is 1.7% [7].

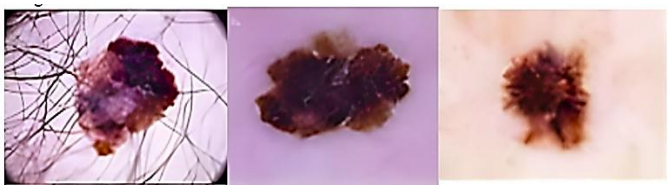

Fig. 1. (a) Melanoma (MEL), (b) Basal Cell Carcinoma (BCC), (c) Squamous Cell Carcinoma (SCC).

Deep learning is commonly employed in the creation of autonomous skin lesion detection systems. Esteva et al. [8] categorized approximately 130,000 clinical images into three categories using deep learning and obtained a 72.1% accuracy rate. Fujisawa et al. [9] showed 92.4% accuracy after detecting 6,000 dermoscopic images using deep learning. As a result, deep learning-based automated diagnosis of melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma shows great promise. Deep learning, on the other hand, refers to a collection of arbitrarily chosen parameters known as hyperparameters [10]. Hyper parameter settings are very variable, and using improper values reduces diagnostic effectiveness. It is difficult to determine the optimal hyperparameter settings.

Recent research [11-15] on dermoscopic image classification has progressively emphasized the utilization of deep learning models, specifically employing the ISIC 2024 and HAM10000 datasets for multiclass classification problems. The ISIC 2024 and HAM10000 datasets are publicly available collections managed by the International Skin Imaging Collaboration (ISIC) and released latest in 2024 to advance

research in the domain. This dataset is widely employed in dermatology and artificial intelligence research, specifically for the development and assessment of algorithms pertaining to the analysis of skin lesions, with an emphasis on pigmented skin lesions. These techniques attempt to address issues such as class disparity, the existence of artifacts, variable size, texture, forms and insufficient contrast between skin lesions and surrounding regions. Using the ISIC 2024 dataset, [16] demonstrated a deep convolutional neural network (CNN) model created especially for multiclass skin cancer classification. Their approach worked far better than well-known transfer learning models like VGG16 and DenseNet. Alsahafi et al. [12] were the first to show Skin-Net, a deep residual network that leverages cross-channel correlation and multilayer feature extraction. Their method worked better for multiclass classification and solved the problem of dataset imbalance when tested on the ISIC 2024 and ISIC-2020 datasets. Another study used both CNNs and transformers to develop a Swin Transformer model for classifying skin lesions [11]. Their method was more sensitive and specific than most standard CNN models when they used the ISIC 2024 dataset [10]. Cauvery et al. [14] created a convolutional neural network model that used transfer learning to sort dermoscopic images from the ISIC 2024 dataset. achieving accuracy of 81.2%. A different study that used transfer learning with the GoogleNet architecture to sort eight types of skin lesions from the ISIC 2024 dataset [15]. CNNs are good at classifying skin lesions into more than one class, as indicated by the model's 90.92% accuracy [15]. Researchers have proven that the Inception V3 architecture, a complex deep learning model, can find important parts of dermoscopic images [16–18]. But there is always room for improvement, especially when it comes to adding new model techniques to specialized datasets.

We have conducted this research that improvised the IV3 approach using dermoscopic skin images. The main goal of this research is to accurately classify the three main stages of skin cancer, namely Squamous Cell Carcinoma, Basal Cell Carcinoma, and Melanoma. This study employed the customized IV3 model alongside the ISIC 2024 and HAM10000 datasets to classify cutaneous skin lesions. Customized IV3 approach is utilized in which data is augmented with respect to size, texture and forms to reduce the issue of overfitting problem and Bayesian hyperparameter tuning to improve identification while reducing the computational complexity. This research work is distinctive as it employs data augmentation and Bayesian tuning in customized manners particularly designed for the dermoscopic image processing of three stages of cancerous human skin.

The proposed customized InceptionV3 pipeline is essentially novel, combining Bayesian hyperparameter optimization as a basic learning mechanism with domain-specific dermoscopic data augmentation, rather than depending on fixed or manually modified parameters as is common practice. Unlike closely comparable state-of-the-art approaches, the model combines transfer learning, probabilistic optimization, and cross-dataset multiclass training into a single end-to-end framework, resulting in increased resilience and generalization.

II. Methods

A. Datasets

This study utilized dermoscopic images from the ISIC 2024 and HAM10000 databases [19, 20] owing to the International Skin Imaging Collaboration's comprehensive repository of lesion images and classifications. Dermoscopic images of 2,000 squamous cell skin lesions, 1,500 Basal Cell Carcinomas, and 1,300 melanomas are included in the collection. Dermoscopic images were chosen at random from the database for this research work. The database images are set of 450 by 600 pixels. To meet the input images size required for deep learning (299×299×3), the images are resized to that size, form and texture and apply random noise to the top and bottom 28 pixels. Notably, the collection is unbalanced, with around half of the images displaying melanocytic nevus. Some of the most popular datasets are shown in Table I.

TABLE I. Popular Publicly Available Datasets for Skin Lesion

Dataset	Data Size	Image Type	Laison Type
ISIC 2024	>400000	Dermoscopy and Medical image	Include: Melanoma (MEL), Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC).
HAM 1OOOO	10,015	Dermoscopy image	Include: Melanoma (MEL), Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC).
Dermnet	23,000	Dermoscopy, pathology	Include: Melanoma (MEL), Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC).
PH2	200	Dermoscopy image	Include: Melanoma (MEL), Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC).

B. Data Processing

To prepare the data for deep learning techniques, a crucial preprocessing step is required, which improves and speeds up the model's performance [21, 22]. The techniques used to standardize and enhance the dataset of input images prior to model training are covered in the next section. Three preparation processes are included in the method: first, the images are resized; second, they are normalized to scale; and third, data augmentation is used to expand the dataset and broaden the model.

C. Data Augmentation

Since data is difficult to get, deep learning models need a large number of labeled samples. Using ABCD rule (asymmetry, border, color, diameter) guideline and data

augmentation is a solution to this issue. By altering images in various ways, including cropping, rotating, flipping, zooming, and shearing, the technique generates new data versions in terms of image size, texture and multiple cancerous forms. Acceptable changes that faithfully capture the inherent differences between dermoscopic image while maintaining their meaning are produced by the applied transforms. The primary objective of data augmentation is to increase the training dataset's diversity, variability, and number of samples. This lessens overfitting and improves the model's ability to generalize. There is a benefit to training models on tiny, irregular datasets.

D. Model Architecture

Fig. 2 shows the Inception V3 architecture, which was a big step forward in deep learning, especially for finding and classifying skin lesions [23]. Google [24, 25] first showed this version of the Inception architecture. It is the third version. Inception V3 has a more complex architecture than the original Inception model, making it a deeper and broader version of the original. It has a lot of "Inception modules" that let it process information well, no matter how big or complicated it is [26].

There are a lot of key layers in the Inception V3 model that work together to quickly gather, enhance, and sort visual data. There are a variety of filters in the convolutional layers, such as 1×1, 3×3, 5×5, and asymmetric ones like 1×7 and 7×1. These filters look for patterns and textures at different scales. The 1×1 convolutions assist cut down on the number of dimensions and speed up the math [23]. Max pooling discovers the most significant characteristics in tiny regions to maintain vital spatial information and cut down on the number of dimensions. Average pooling, on the other hand, makes feature maps more consistent and, when applied globally, substitutes dense layers to stop overfitting [27]. The concatenation mechanism pulls together outputs from many convolutional and pooling paths in each Inception module. This lets the network collect both fine and coarse input at the same time. Dropout switches off certain neurons while training to help the model generalize better and reduce the chance of overfitting. At the end, a completely connected layer puts all the learnt characteristics into one vector. The last softmax layer then changes this output into class probabilities, which makes it easier to put items into the right groupings, including melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma [27, 28].

Better performance: this model is more accurate and works faster than the ones that came before it, especially when it comes to identifying big images. It became more accurate while consuming less computational resources than older versions. Inception V3 is notable for taking huge convolutions and breaking them down into smaller, easier-to-manage steps. You may split a 5×5 convolution into two 3×3 convolutions [29, 30]. This cuts down on the number of parameters, which helps keep the model from overfitting and makes it easier to analyze. Inception V3 has a nice way to make the grid smaller without causing a representational bottleneck. We were able to achieve this by utilizing convolution with a stride instead of pooling to make the grid smaller. Batch normalization is a technique that changes and scales the activations of a layer to make the input to that layer the same for all layers [23]. Batch normalization is a big part of the design. This strategy improved the training process faster and introduced some regularization, which made dropout less important. Inception V3 has been used a lot for facial recognition, object detection, and sorting images into groups. Because it worked so well, it could be used for both academic study and real-life situations, even on devices with low computing power. The evolution of CNNs took a big stride forward with Inception V3. It found the proper mix between how well the model worked and how well it used computers, which made it possible for the field to go forward [29]. The main reason for using the Inception V3 architecture in this research work is that it works very well at categorizing malignant skin lesions [20,21]. For precise cauterization of malignant skin cancerous stages, this approach is highly rated.

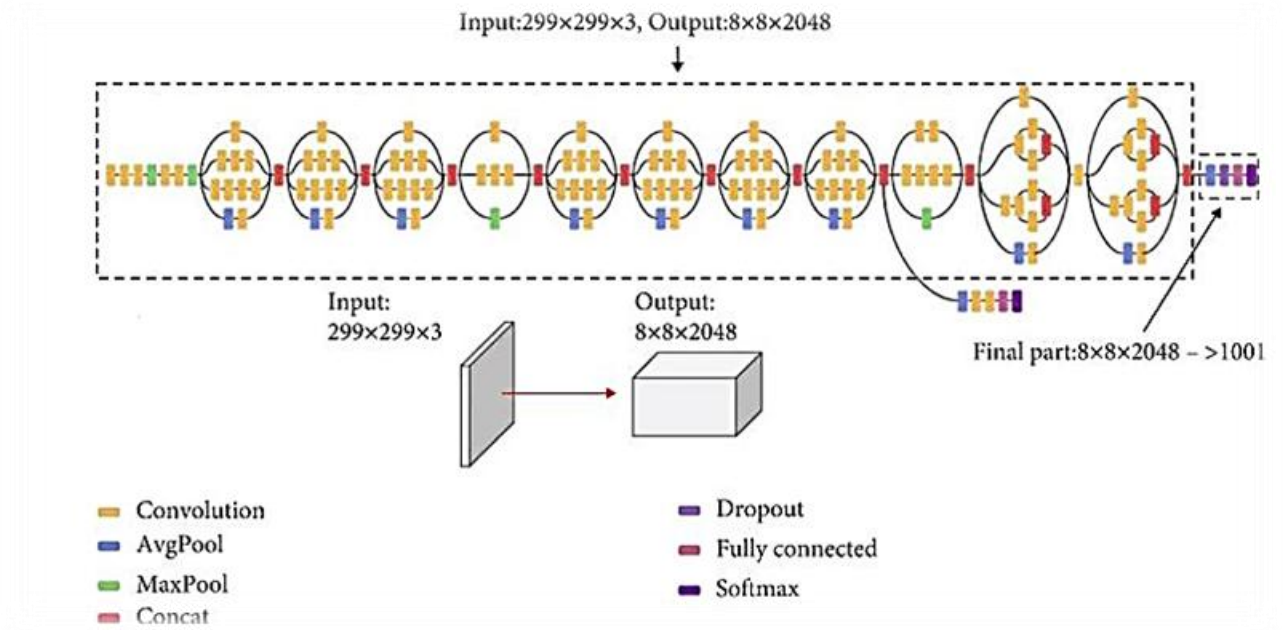

Fig. 2. General architecture of Inception V3 [23].

E. Bayesian Tuning

Bayesian tuning is an optimized statistical approach that adopts the best suited hyperparameter for skin cancer classification. Bayesian optimization creates a surrogate model $M(\theta)$ for the objective function and uses an acquisition function $a(\theta|M)$ to find the next hyperparameter point to evaluate [27]. The surrogate model $M(\theta)$ is modeled as a Gaussian process (GP): $M(\theta) \sim \text{GP}(\mu(\theta), k(\theta, \theta'))$, where $\mu(\theta)$ represents the mean function and $k(\theta, \theta')$ denotes the covariance (kernel) function. The acquisition function $a(\theta|M)$ reconciles exploration (investigating uncharted portions of the hyperparameter space) with exploitation (concentrating on areas with established favorable outcomes) [27]. The current work conducted hyper-parameter fine-tuning by Bayesian optimization and Inception V3 model to determine the optimal parameter configurations shown in Table II. The objective of Bayesian tuning in modeling was to enhance model parameters via a Bayesian probabilistic methodology. The main goals were to improve the model's performance, reduce overfitting or underfitting, optimize parameters well, speed up processing, and make it match the data better. explores to identify optimal parameter combinations, accounting for trade-offs and responding to data complexities.

F. Proposed Model

This research implements the following proposed model for classification of Melanoma, Basal Cell Carcinoma, and Squamous Cell Carcinoma skin lesion shown in Fig. 3. The figure in the proposed model shows a complete pipeline for classifying skin lesions using a customized Inception V3 architecture that has been improved with Bayesian optimization. The illustration shows the main functional phases of the model's process, from data intake to final classification. Each block represents one of these phases.

The first block, "Input Image," shows dermoscopic images of skin lesions that were taken from the ISIC 2024 and HAM10000 databases to make the dataset. These dermoscopic images show three types of cancer: melanoma, Basal Cell Carcinoma (BCC), and Squamous Cell Carcinoma (SCC). Inception V3 needs images that are 299×299×3 pixels big.

Then, the "Data Preprocessing" process is done to get the raw data ready for model training. Various techniques such as scaling, normalization and noise reduction are used in data processing procedure so that dermoscopic images have equal size and properly aligned for further processing.

The "Data Augmentation" block extends the dataset by using various techniques such as zooming the image, flipping the image, rotating and cropping the image reducing overfitting effect, more training data and better model performance for recommended three stages of skin lesion predictions.

The most important is the fourth block which implements the "Customized Inception V3 Deep Learning Model". The model takes previous stages enhanced dermoscopic images that goes through various convolutional, pooling and concatenation layers to generate various lesion patterns. Dropout layers reducing the effect of overfitting whereas Batch Normalization makes the learning process faster for the customized recommended model.

TABLE II. INCEPTION V3 AND BAYESIAN HYPERPARAMETERS

Hyperparameters	Optimized Value
Input Image size	299 × 299 × 3
Input Type	RGB Dermoscopic Images
Learning Rate	0.0001
Dropout Rate	0.3
Optimizer	Adam
Batch Size	32
Epochs	200
Surrogate Model	Gaussian Process (GP)

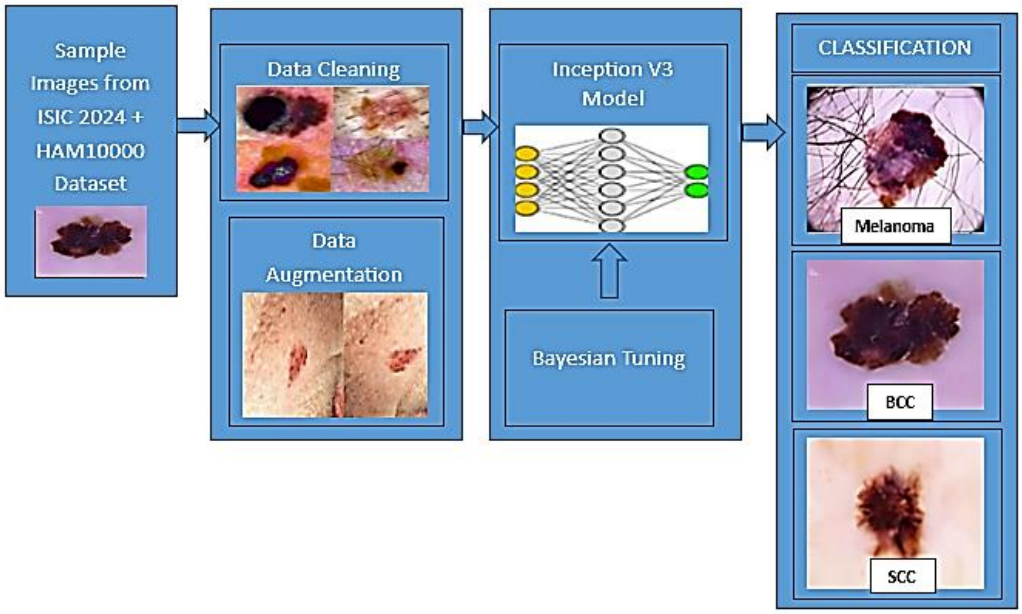

Fig. 3. Proposed model for malignant skin lesion classification.

The "Bayesian Tuning" module then tweaks the model's parameters, such the learning rate, dropout ratio, batch size, and choice of optimizer. Using Bayesian tuning optimization and a Gaussian Process-based surrogate model, we discovered the optimum hyperparameters for the fine-tuned Inception V3 model. The optimized parameters are an input image size of 299×299×3 (which is the network's default setting), a learning rate of 0.0001 to make sure that convergence is stable, a dropout rate of 0.3 to avoid overfitting, and the Adam optimizer, which was chosen because it can work with different learning situations. The batch size was adjusted to 32 to make calculating faster and the gradient more stable. To give enough learning iterations without overfitting, the number of epochs was set to 200. The best values were found through a number of iterations based on the Bayesian framework, which used the model's accuracy and loss feedback to gradually improve the search for the best parameters.

The "Fully Connected + Softmax Layer" turns the high-level, abstract data into probabilities for classification. The fully connected (dense) layer combines what it has learned, and the softmax activation turns that information into probabilities for the three classes (Melanoma, BCC, and SCC).

The "Output Layer" performs three stages of skin cancerous classification based on accuracy, precision, sensitivity, specificity and F1-score representing the overall performance of the recommended hybrid approach.

G. Performance Evaluation

The assessment of recommended cancerous skin lesion model is based on adopting IV3 and Bayesian tuning hybrid approach that works on four main performance metrics in dealing with unbalanced dermoscopic images represent as accuracy, precision, recall, and F1 score.

Accuracy (AC) shows how well the model is overall working taking both true positive and true negative values for accurate predictions. The formula for calculating accuracy is:

$$AC = \frac{T_P + T_N}{T_P + F_N + T_N + F_N} \quad (1)$$

Precision (PR) represents the true positive values upon total positive values. This shows how well the model predict three skin cancerous stages while eliminating other category accurately. The formula is represented as:

$$PR = \frac{T_P}{T_P + F_P} \quad (2)$$

Sensitivity (S) means identifying every actual positive cases. It also represents as true positive rate of overall model. When the model finds all examples of a certain illness, it makes it easier to remember how to group skin problems. It is represented as:

$$S = \frac{T_P}{T_P + F_N} \quad (3)$$

Using harmonic mean calculations, the F1 Score combines accuracy and recall into one figure. The F1 Score is quite helpful when looking at medical image dataset since the classes in these datasets are typically not evenly distributed. The method preserves an appropriate balance between false negatives and false positives:

$$F1\ Score = \frac{2 * P_R * S}{P_R + S} \quad (4)$$

Specificity is the true negative rate, which shows the percentage of benign lesions that were correctly identified as benign instead of being classified as malignant. This is a crucial performance indicator utilized in conjunction with sensitivity (true positive rate) to assess the accuracy of classification models.

$$Sp = \frac{T_N}{F_P + T_N} \quad (5)$$

III. Results and Discussion

This work is focused in classification of 3 significant types of skin cancerous disease (Melanoma, Basal Cell Carcinoma and Squamous Cell Carcinoma). This work employed the Inception V3 pre-trained model to categorize images into three separate classifications (Melanoma, Basal Cell Carcinoma and Squamous Cell Carcinoma) utilizing the ISIC 2024 and HAM10000 dataset. During simulation, we have considered 70% of the data set for training purpose and rest is considered for testing purpose. We executed our proposed model for 3 different cases by considering without augmentation, with augmentation, and with augmentation along with Bayesian tuning to analyze the shortcomings and improve the efficiency of skin cancerous lesion classification.

A. Case I (Without Augmentation of Input Images)

The model performed inconsistently in the first case, which did not involve data augmentation. It performed quite well at correctly identifying three classes, but it lacks accuracy while identifying the other two and frequently confused one class for another while being validated. The model could be overfitted because of the lack of input data variability. shown is Table III and accuracy curve plot results for all three classes are shown in Fig. 4.

TABLE III. Dataset Consideration for Case 1

Skin Cancer	Total Images	Training	Testing
Melanoma	1300	910	390
BCC	1500	1050	450
SCC	2000	1400	600

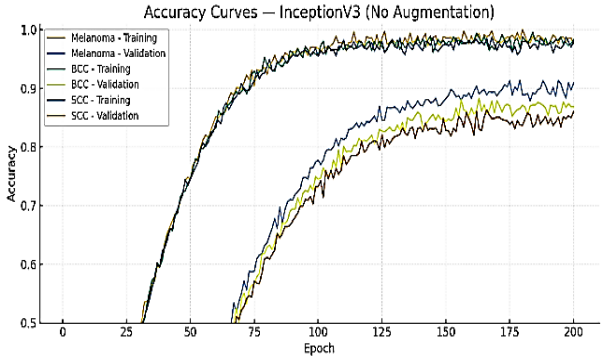

Fig. 4. Accuracy curve of MEL, BCC, and SCC for Case 1.

B. Case II (With Augmentation of Input Images)

The introduction of data augmentation in the second case, which involved training the model with a more diverse dataset, resulted in a significant enhancement in the accuracy level. This technique mitigated the model's susceptibility to minor data variations, thereby improving recognition across all three skin lesion types. The implementation of data augmentation stabilized validation accuracy and diminished overfitting. The increase in accuracy and reduction in overfitting is due to enhancement in feature extraction from the augmented data and improvement in the learning rate of our proposed model. Although a gap persists between training and validation accuracy, it is less pronounced. Table IV represents dataset consideration for CASE II and accuracy curve plot results for all three classes are shown in Fig. 5.

TABLE IV. DATASET CONSIDERATION FOR CASE II

Skin Cancer	Total Images	Training	Testing
Melanoma	1625	1138	487
BCC	1875	1313	563
SCC	2500	1750	750

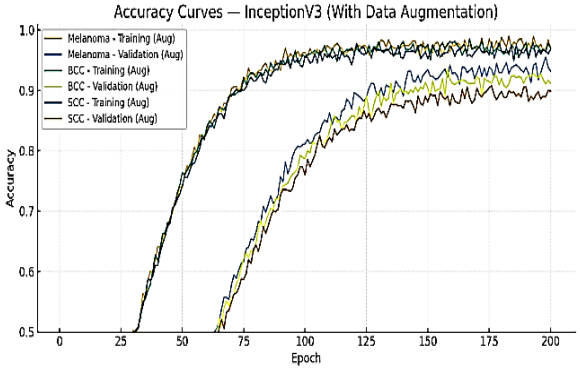

Fig. 5. Accuracy curve of MEL, BCC, and SCC for Case II.

C. Case III (With Augmentation along with Bayesian Tuning)

The third case used Bayesian tuning in addition to data augmentation. Bayesian tuning slightly enhanced the model's decision-making by including the confidence of its predictions and provides much smoother accuracy prediction with a little less variation. This resulted in a substantial increase in accuracy, as the model now faultlessly recognizes all three classes that it previously struggled with. The incorporation of Bayesian hyperparameter tuning alongside data augmentation resulted in enhanced stability of validation accuracy, exhibiting less volatility and a diminished disparity between training and validation accuracy. The dataset used is same as used in CASE II with accuracy curve plot results for all three classes are shown in Fig. 6.

D. Comparison of Performance Metrics

The sample dataset from ISIC 2024 and HAM 100000 demonstrates that our suggested approach, which integrates data augmentation techniques along with the Inception V3 module, and Bayesian tuning significantly enhances performance across all evaluation metrics: accuracy, sensitivity, precision, specificity, and F1 score. Fig. 7 and Table V represent overall model performance key metrics results in terms of Accuracy, Precision, Sensitivity, Specificity and F1 score. In general, these findings indicate that the suggested model demonstrates top-tier performance in classifying multiple types of skin cancer and can proficiently differentiate between melanoma, BCC, and SCC.

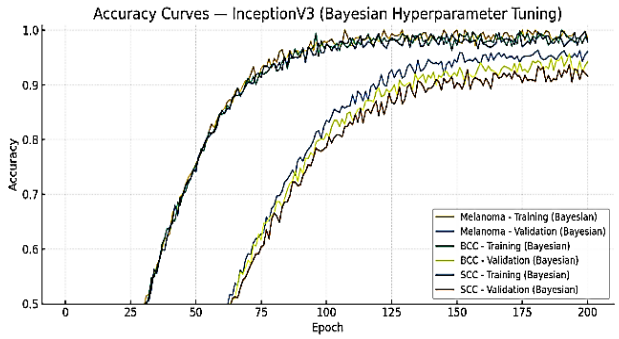

Fig. 6. Accuracy curve of MEL, BCC, and SCC for Case III.

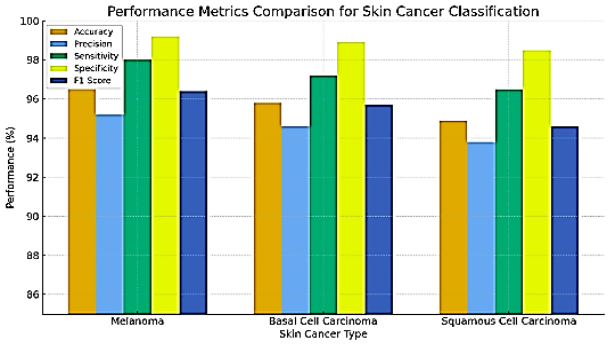

Fig. 7. Performance metrics comparison for MEL, BCC, and SCC skin cancer classification.

TABLE V. PERFORMANCE METRICS COMPARISON FOR MEL, BCC AND SCC SKIN CANCER CLASSIFICATION

	MEL	BCC	SCC
Accuracy	96.5%	95.8%	93%
Precision	95%	94.5%	93.8%
Sensitivity	98.2%	97.2%	96.4%
Specificity	99.2%	98.8%	98.5%
F1 Score	96.5%	95.8%	94.8%

The figure and table results show combined average accuracy of 95.1 percent, a precision of 94.42%, a sensitivity of 97.3 percent, a specificity of 98.8 percent, and an F1 score of 95.7 percent were achieved by the suggested model for the combined datasets. This indicates that the model performed substantially better than the methodologies that were previously used and offered a diagnosis of pigmented skin lesions that were both more accurate and consistent.

IV. CONCLUSION

The current study shows a significant improvement in classification accuracy relative to the standard pre-trained Inception V3 model, exceeding previous recent research efforts in dermatology. We have performed extensive simulations to

access the performance of IV3 architecture along with augmentation techniques and Bayesian tuning optimization. With a combined accuracy of 95.1% and great sensitivity and specificity, the model outperforms conventional transfer-learning techniques, according to experimental findings on the combined ISIC 2024 and HAM10000 datasets. These results validate the resilience and generalization capacity of the model and demonstrate the scientific utility of combining Bayesian tuning with deep CNN architectures which improved the overall accurate classification prediction of skin cancer stage diagnosis. The holistic approach significantly enhances the prediction of different stages of human skin cancer which demonstrate the importance of deep learning techniques. This customized model shows the promising nature which can ease in identification of cancerous skin diseases. The suggested framework has a high potential for use in computer-aided dermatological systems, enabling early and accurate diagnosis of melanoma, basal cell carcinoma, and squamous cell carcinoma and so leading to better clinical decision-making.

V. Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

References

[1] Mohammed, S. S., & Al-Tuwaijari, J. M. (2021). Skin Disease Classification System Based on Machine Learning Technique: A Survey. IOP Conference Series: Materials Science and Engineering, 1076(1), 012045. https://doi.org/10.1088/1757-899x/1076/1/012045.

[2] Thompson JF, Scolyer RA, Kefford RF: Cutaneous melanoma. Lancet. 365(9460), 687–701, 2005.

[3] American Joint Committee Cancer Staging Manual. 6th edn. Springer-Verlag, New York, 2002.

[4] Erdmann F, Lortet-Tieulent J, Schüz J, Zeeb H, Greinert R, Bre itbart EW, Bray F: International trends in the incidence of malig nant melanoma 1953-2008- are recent generations at higher or lower risk? Int J Cancer. 132(2), 385–400, 2013.

[5] Rembielak A, Tagliaferri L. Non-melanoma skin cancer. Boca Raton: CRC Press; 2023.

[6] Rosendahl C, Marozava A. Dermatoscopy and skin cancer: A handbook for hunters of skin cancer and melanoma, updated edition 2023. Banbury: Scion Publishing; 2023.

[7] Australian Institute of Health and Welfare. Cancer data in Australia (web report). Available from: https://www.aihw.gov.au/reports/cancer/cancer-data-in-australia/contents/about.

[8] Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, Thrun S: Dermatologist-level classi cation of skin cancer with deep neural networks. Nature. 542(7639), 115–118, 2017.

[9] Fujisawa Y, Otomo Y, Ogata Y, Nakamura Y, Fujita R, Ishitsuka Y, Watanabe R, Okiyama N, Ohara K, Fujimoto M: Deep learn ing-based, computer-aided classi er developed with a small data set of clinical images surpasses board-certi ed dermatologists in skin tumour diagnosis. Br J Dermatol. 180(2), 373–381, 2018.

[10] Waqar, Maimoona, Afsheen Khalid, Sohail Nawaz Sabir, Fazal Malik, and Dilawar Khan. "A Comparative Study of Convolutional Neural Networks (CNN) and Inception V3 for Facial Skin Disease Classification." *Kashf Journal of Multidisciplinary Research* 2, no. 03 (2025): 232-258.

[11] Ayas S. Multiclass skin lesion classification in dermoscopic images using swin transformer model. Neural Comput Appl 2023;35(9):6713-6722.

[12] Alsahafi YS, Kassem MA, Hosny KM. Skin-Net: A novel deep residual network for skin lesions classification using multilevel feature extraction and cross-channel correlation with detection of outlier. J Big Data 2023;10(1):105.

[13] Houssein EH, Abdelkareem DA, Hu G, et al. An effective multiclass skin cancer classification approach based on deep convolutional neural network. Clust Comput 2024;27:12799-12819.

[14] Cauvery, Siddalingaswamy, Pathan S, et al. A multiclass skin lesion classification approach using transfer learning based convolutional neural network. In: 2021 Seventh International conference on Bio Signals, Images, and Instrumentation (ICBSII). Chennai; 2021.

[15] Kassem MA, Hosny KM, Fouad MM. Skin lesions classification into eight classes for ISIC 2024 using deep convolutional neural network and transfer learning. IEEE Access 2020;8:114822-114832.

[16] Nugroho ES, Ardiyanto I, Nugroho HA. Boosting the performance of pretrained CNN architecture on dermoscopic pigmented skin lesion classification. Skin Res Technol 2023;29(11):1-10.

[17] Nugroho ES, Ardiyanto I, Nugroho HA. Comparative performance of pre-trained CNN architectures on dermoscopic pigmented skin lesions classification. In: 3rd International Conference on Electronic and Electrical Engineering and Intelligent System (ICE3IS). Yogyakarta; 2023.

[18] Gopikha S, Balamurugan M. Regularised layerwise weight norm based skin lesion features extraction and classification. Comput Syst Sci Eng 2023;44(3):2727-2742.

[19] Tschandl P, Rosendahl C, Kittler H: The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. Sci Data. 5, 180161, 2018.

[20] Tschandl P, Rosendahl C, Kittler H: The HAM10000 dataset, a large collection of multi-source dermatoscopic images of com mon pigmented skin lesions. Sci Data. 5, 180161, 2018.

[21] Szegedy C, Vanhoucke V, Ioffe S, et al. Rethinking the inception architecture for computer vision. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Las Vegas; 2016.

[22] Mandeel, Bahaa Salih, Manar Raad Abdalhassan, Diyaa Kareem Abd-Alhmza, and Muhtadi Thamer Mousa Raad. "A robust CNN Deep Learning and InceptionV3 model Techniques for Enhanced Skin Cancer Detection." *Journal of Al-Qadisiyah for Computer Science and Mathematics* 16, no. 4 (2024): 309-317.

[23] Ramaneswaran, S., Srinivasan, K., Vincent, P. M. D. R., & Chang, C. Y. (2021). Hybrid Inception v3 XGBoost Model for Acute Lymphoblastic Leukemia Classification. Computational and Mathematical Methods in Medicine, 2021. https://doi.org/10.1155/2021/2577375.

[24] Nugroho, Erwin S., Igi Ardiyanto, and Hanung A. Nugroho. "Enhancing dermoscopic pigmented skin lesion classification: A refined approach using the pre-trained Inception V3 architecture." *Narra J* 5, no. 2 (2025): e1852-e1852.

[25] Waqar, Maimoona, Afsheen Khalid, Sohail Nawaz Sabir, Fazal Malik, and Dilawar Khan. "A Comparative Study of Convolutional Neural Networks (CNN) and Inception V3 For Facial Skin Disease Classification." *Kashf Journal of Multidisciplinary Research* 2, no. 03 (2025): 232-258.

[26] Mamun, Md Al, Md Solaiman Kabir, Morium Akter, and Mohammad Shorif Uddin. "Recognition of human skin diseases using Inception V3 with transfer learning." *International Journal of Information Technology* 14, no. 6 (2022): 3145-3154.

[27] Nagaoka, Takashi. "Hyperparameter optimization for deep learning-based automatic melanoma diagnosis system." *Advanced Biomedical Engineering* 9 (2020): 225-232.

[28] Chaurasia, Shubham, and Shiwangi Choudhary. "Skin Lesions Classification Using Deep Ensemble Learning Model of VGG-16, ResNet-50 and Inception V3." (2025).

[29] Reddy, Kunam Subba, Monelli Ayyavaraiah, B. Lalithadevi, A. Mohanadevi, Sreenivas Reddy Sagili, and V. C. Bharathi. "Implementation of InceptionV3 Model for Skin Disease Detection and Classification." In *2025 6th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI)*, pp. 1479-1485. IEEE, 2025.

[30] Bhaskar, Rajeev Kumar, and Balasubramaniam Kumaraswamy. "Early Detection of Melanoma Through Deep Learning-Based Skin Lesion Classification Using VGG16 and InceptionV3." In *2025 International Conference on Automation and Computation (AUTOCOM)*, pp. 1333-1339. IEEE, 2025.