

Transfer Learning-Based Skin Cancer Classification Using a Modified VGG19 Network

Harendra Singh

PhD Scholar CSE

LNCT University

Bhopal, India

harendra.cse07@gmail.com

Dr.Divyarth Rai

Prof. CSE Dept.

LNCT University

Bhopal, India)

divyarthrai@gmail.com

Abstract—Skin cancer continues to be one of the most common and potentially fatal types of cancer globally, with the need for early and precise diagnosis to enhance patient outcomes. This article introduces a novel method of automated skin cancer classification based on a Modified VGG19 deep learning model. Embracing the philosophy of transfer learning, the model utilizes pre-trained weights of ImageNet with selective fine-tuning of the last layers to better fit the unique characteristics of skin cancer images. Also, a dual transfer learning approach was utilized with retraining the early layers of a pre-trained model AlexNet to improve detection of lesion boundaries. The model was trained and tested on the publicly available HAM10000 dermoscopic image database with 5-fold cross-validation. The model with the suggested approach attained superior performance with an average validation accuracy of 99.07%. The proposed technique proved to be more accurate and robust when compared to other current existing classification methods. The results imply that Modified VGG19 model, augmented with an adapted transfer learning framework, is exceedingly suitable for the diagnosis of skin cancer and is strongly promising for real-world clinical use.

Keywords— *Skin Cancer, VGG19, ImageNet, transfer learning.*

I. INTRODUCTION

Skin cancer ranks between the most common cancer in the United States [1, 2]. Studies show that one in five Americans can develop skin cancer during their lifetime [3], stated to be annually in about 95,000 new cases [4]. Melanocytes, pigment-cord cells responsible for the skin or brown color [5], when they grow uncontrollably, can cause cancer, resulting in an aggressive yet less common form of melanoma-skin cancer [5]. Estimates suggest that about one million Americans are living with melanoma [6], and the disease claims about 20 lives every day in the US [7]. Estimates indicate that the U.S. About 197,700 persons will be diagnosed with melanoma in 2022 [6]. Additionally, about three million American non-melanoma are affected by skin cancer, such as basal cell carcinoma (BCC) and squamous cell carcinoma (SCC) [4]. Importantly, early detection of melanoma is 99% of survival rate [6], which outlines the important requirement for early diagnosis of skin cancer.

Traditionally, medical professionals diagnose skin cancer through visual examination, a method that can be both time and intensity and may be prone to errors [8]. Only 6% of skin cancer cases are correctly identified as melanoma during visual inspection. Dermoscopy, a technique that increases the visibility of skin microstructure and colors through lights, provides better clinical accuracy [8, 9]. However, dermoscopic accuracy depends a lot on the experience and expertise of the tester due to the similarity in the color, size, and similarity in the wound. These factors can make inconsistent diagnosis in various physicians, which highlight the requirement of a computer-aided diagnostic system to enhance early identity.

Computer-obstructed diagnosis of skin cancer usually consists of several stages: image, pre-processing, division, convenience and capturing classification [10, 11]. However, challenges such as skin tone, wound texture and shape and artifacts such as hair, air bubbles, shadows, and calibration marks complicate the division and classification functions [12, 13].

This study focuses on differences between melanoma and non-melanoma skin lesions through image classification. In recent years, machine learning (ML) techniques have greatly improved 15–20% [14] in the accuracy of automatic skin cancer detection. Of these, deep education - a sort of ML, famous for its effectiveness in image recognition - has performed extraordinary performances in skin wound analysis and classification [15, 16]. The next section provides a comprehensive review of research that employs deep learning for skin cancer classification.

II. LITERATURE REVIEW

The work presented in [17] proposes a functioning to classify skin lesions using fine-tuned neural networks. To address data imbalance, resampling techniques are applied to skin wound images. A hybrid model by combining Densnet and U-Net is trained for partition purposes, and resulting in fine for architectural classification. The Enkoder component of the partition model is availed to classify seven different types of skin diseases. This approach received a balanced accuracy of 0.836 on test dataset and 0.840 on verification dataset.

In [18], an advanced preprosanging method is introduced that automatically increases skin wound images before partition. This method removes unwanted artifacts such as hair, gel, bubbles and specular reflections. A novel is proposed to detect and mask hair in vowellet-based algorithm images. In addition, the wound contrast is improved using an adaptive sigmoid function, which adjusts the localized intensity distribution. An accurate division technique is then used to separate the wound from healthy tissue. This model was validated using the European Dermoscopy image database.

A study in [19] focus on classifying skin lesions using intensive learning, especially firm nerve network (CNN). The dataset is the Ham10000, which includes 10,015 images from seven skin wound categories. The CNN-based model trained in the study acquired an accuracy of 78%. Another study presents a completely firm dark nerve network for cementic division at the pixel level. The network consists of an encoder, decoder, and a pixel-wise classification layer, which contains encoders with encoders using the determined layers of VGG-16. The decoder rebuilds full-resolution feature maps from the output of the encoder.

In another approach [20], the focus on deep learning for skin lesion classification using CNNs is focused on. By using the HAM10000 dataset, the author applies methods of learning and receives 88% accuracy.

The study in a machine learning pipeline for skin cancer classification [21], which includes preprocessing, division, convenience extraction and classification. Feature extraction techniques include ABCD rules, gray-level cum-phenomenon matrix (GLCM), and oriented gradients (HOGs). Using a dataset from ISIC Archive which includes 328 benign and 672 deadly melanoma images, support vector machine (SVM) classifier, 97.8% accurate and 0.94 AUC yield. K-NEAREST neighbors (KNN) achieved 86.2% sensitivity and 85% uniqueness.

The strategy mentioned in [22] focuses on skin cancer detection and classification using traditional machine learning approaches. The technology of an unprotected learning technique, the class cluster, achieved a classification rate of 52.63%. When melanoma is applied to detect, the-shadow makes two clusters-for a cancer and for a non-cancer data. The classification accuracy ranged from 60% to 75% back to the back propagation nerve network (BPNN) and from 80% to 90% for SVMs, indicating that SVMS K-means improves both means and BPNN.

The approach in [23] emphasizes intensive learning-based classification using CNN. ISIC dataset was used, as well as data growth, generalization and transfer learning techniques such as Inceptionv3, Resanet, VGG-16 and Mobilent.

In [24], a supervised teaching structure is used to classify skin lesions with a strong focus on computer-aided diagnosis (CAD). Techniques such as wound division, hair detection and pigment network analysis have been integrated with MAP estimates. The proposed system acquired 86% accuracy.

Finally, the work in [25] examines skin cancer detection and classification using deep learning models. Dataset consists of Ham10000 (10,015 images in seven categories) and PH2 (200 wound images). The model was trained using architecture such as Mobilent and VGG-16, in which data growth applies. Mobilent gained 81.52% accuracy, while VGG-16 reached 80.07% [26].

III. PROPOSED METHODS

In this study, we focused on developing and training deep nerve network using images of skin lesions. A deep firm nerve network (CNN) was trained on a dataset with various skin wound images. To customize the training process, we used adam optimizer and include initial restrictions to prevent overfitting. All experiments were performed on Google Colaboratory platforms [27]. The last layer of the model was designed to handle binary classification. To reduce the risk of increasing loss, a random dropout technique was applied during training.

A. Convolutional Neural Network (CNN)

Deep learning has greatly expanded the capabilities of machine learning in real-world applications. In these methods, many hidden layers are used to learn and mapping complex features, removing the requirement of manual feature engineering - one of the major benefits of deep learning. In this context, convisional layers play an important role as the main component of CNN, one of the most powerful deep learning models. Various CNN architecture can be employed to process input images and extract intermediate convenience representation. Pooling layers, such as maximum-pooling used in our models, help reduce the dimensions of these feature maps and reduce the overall number of parameters. After the pooling stages, a fully associated layer is added to convert multi-dimensional data into one-dimensional format. Finally, a softmax layer asserts binary classification by assigning the label (0 or 1) corresponding to the normal and cancer skin wound categories, [28]. The composition of the model is painted in Figure 1.

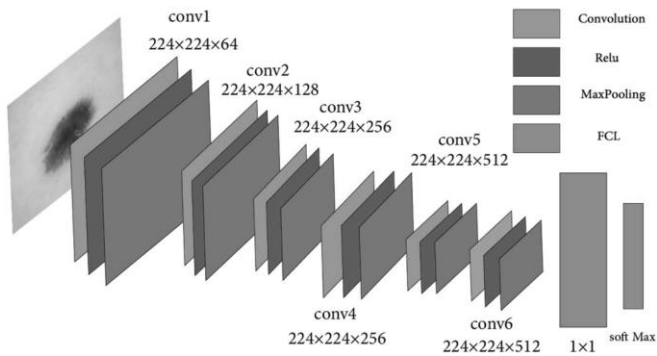


Fig. 1. A view of the customized CNN architecture

B. Model Architecture

The model as proposed was created and run on the Kaggle environment, as well as other benchmark networks for comparison. The foundation of our model is the VGG19 architecture, whose frozen weights [27] pre-trained on the ImageNet dataset we used. As done with standard transfer learning procedures, we fine-tuned and trained the last two layers of the network to customize it for our particular medical image classification task. It should be noted that our dataset is made up of dermatological images, which is not one of the 1,000 ImageNet classes [28] in an explicit way.

In order to better deal with the special features of our dataset, we also re-trained the first three layers of a pre-trained model AlexNet [29]. This strategic adjustment greatly improved the network's performance for the recognition and segmentation of lesion boundaries, as evidenced by our experimental results. During training, both the first three layers and last two layers were updated to maximize model performance. This effectively constitutes a two-stage transfer learning strategy. The overall structure, shown in Figure 2, highlights our tailored transfer learning framework, which enhances lesion detection accuracy, improves convergence speed, and attains high classification performance.

C. Transfer learning with CNNs and frozen layers using imagenet

Taking advantage of pre-educated Convolutional Neural Network (CNN) with imagenets and freezing the early layers is a widely adopted transfer strategy. This technique uses generalized visual knowledge obtained from large -scale imagenet dataset to increase performance on new, potential small datasets. By freezing the early layers-usually the first six-model retains its strong feature extraction capabilities, preventing these layers from being modified during fine-tuning.

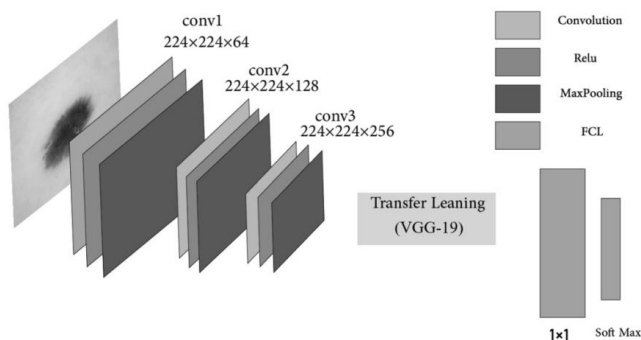


Fig. 2. Proposed transfer learning to customize CNN

Major stages include

Using a pre-instructed network: Start with a CNN architecture such as a ResNet, Inception, or mobilNet that is trained on the imageNet. These models have already learned diverse and transferred features from a huge range of image classes.

Freezing layers: The initial firm layers (eg, earlier 6) are frozen, which means their parameters remain unchanged during the training process. This avoids renovation gradients for these layers, protecting their learned characteristics.

Fixing the model: Only the remaining unfriendly layers and any newly added layers are trained using the new dataset. This allows the model to be adapted to the work-specific pattern while benefiting from the general characteristics extracted by frozen layers.

Advantage of freeze layers

The initial CNN layers usually learn universal patterns such as edges and textures, which are relevant in various visual functions. Freezing these layers prevents the erosion of these common characteristics, accelerates training, and especially

reduces the beneficial when working with limited data. Low parameters are updated, resulting in sharp convergence. Helps maintain performance on small datasets. Uses a strong earned representatives, improving the adaptability of the model for new data.

IV. RESULTS AND DISCUSSION

This section presents a comprehensive analysis of the results obtained from implementing the proposed Modified VGG19 model for skin cancer image classification. The performance was evaluated through a 5-fold cross-validation approach, ensuring robustness and generalizability of the model across various subsets of the dataset. The evaluation metrics used for performance assessment include training and validation accuracy, loss, macro precision, macro recall, and area under the ROC curve (AUC).

This research experiments were done using Kaggle platform and its deep learning library. Referred to the proposed model modified CNN network with VGG19 was tested at HAM10000 [30] dataset to classify the types of seven skin cancer. The performance of the system was evaluated against the famous benchmark and measured using several major matrix.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Recall (Sensitivity)} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{Specification} = \text{TN} / (\text{TN} + \text{FP})$$

$$\text{F1 score} = 2 \times (\text{precision} \times \text{recall}) / (\text{accurate} + \text{recall})$$

$$\text{Accuracy} = (\text{TP} + \text{TN}) / \text{Total Samples}$$

Where: TP (true positive): in correctly identified cancer cases and FN (wrong negative): Cancer cases missed

A. Dataset description

In this study, dermoscopic images have been obtained from skin cancer MNIST: HAM10000 dataset [30], which is publicly made available by international skin imaging cooperation (ISIC) and hosted on Kaggle [31]. This dataset has 10,015 high-resolution images of pigmented skin lesions collected from various patient populations. For experimental evaluation, dataset is divided into training and testing the most in the ratio of 80:20.

Dataset contains seven types of skin lesions sample image given in figure 3:

1. Actinic keratoses
2. Gentle keratosis such as lesions (BKL)
3. Basal cell carcinoma (BCC)
4. Dermatophybrooma
5. Melanoma (mEL)
6. Melanocytic navy (NV)
7. Vascular wound (vasc)

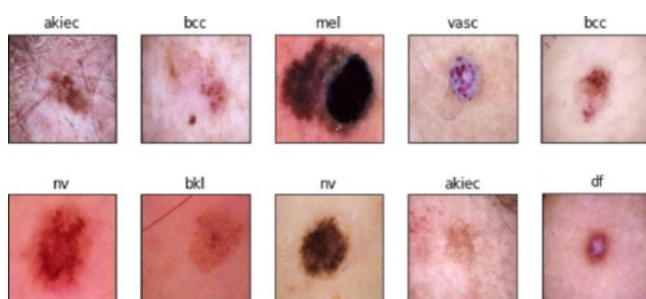


Fig. 3. Shows representative samples from each category.

B. Data Preroposing

Effective preprocess is important to highlight the minor visual characteristics in dermoscopic images while reducing irrelevant noise. Adaptive mean filters are used to remove noise, which improves image quality. Additionally, data growth technology - such as rotation, flipping and scaling - is applied to increase the size and variety of training sets. This reduces the risk of overfitting and improves the ability of the model to normalize. The enhanced dataset helps the model learn more strong and irreversible features.

C. K-fold cross validation

To ensure a strong and fair evaluation of the ability of the proposed model to classify skin lesions on unseen data, we applied the K-fold cross-validation technology. This method allowed us to correctly assess the normalization performance of the model by repeatedly training and verification of various data division. In addition, the use of K-fold cross-validation featured fine-tuning of hyper-parameters, which contributes to optimal model performance.

NUMBER OF SAMPLES IN EACH CLASS

Class Label	No. of Samples
0	327
1	514
2	1099
3	115
4	6705
5	1113
6	142

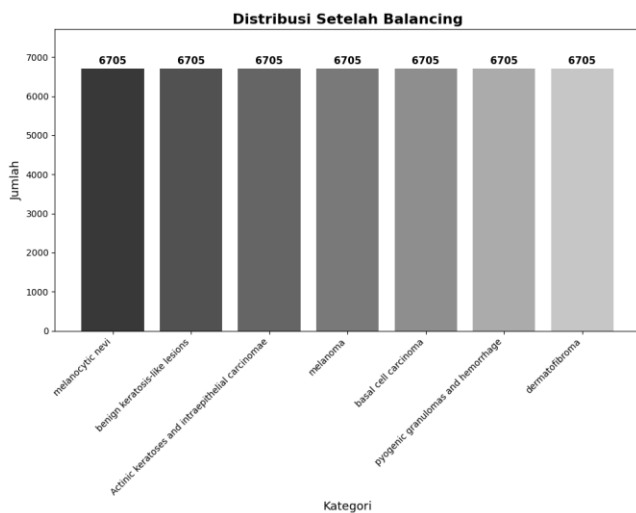


Fig. 4. HAM10000 Dataset Balancing distribution across all classes

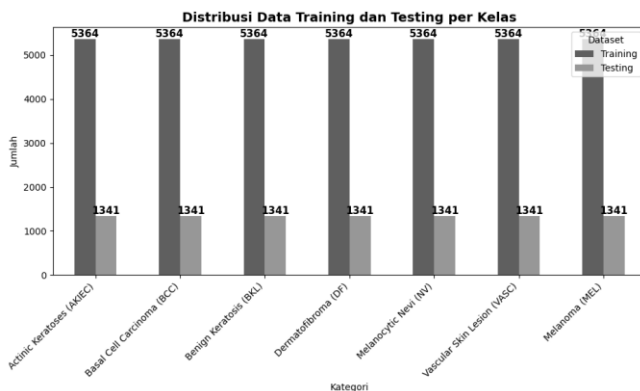


Fig. 5. HAM10000 Dataset Train and Test data distribution for all classes

D. Fold-wise Performance Evaluation

The model was trained and validated across five distinct data folds. A summary of the best performance per fold is outlined. Fold 1 achieved a training accuracy of 97.14% and validation accuracy of 97.21%, with a macro precision and recall of 96.23% and 96.16%, respectively as shown in figure 6. The macro AUC was 0.9960, indicating strong discriminatory power even at this fold. Fold 2 showed improved performance with a training accuracy of 99.29% and a validation accuracy of

98.54%. Precision and recall values both stood at 98.53%, and the AUC improved further to 0.9993, confirming high classification capability. Fold 3 demonstrated near-perfect results with training accuracy of 99.81% and validation accuracy of 99.72%, and the model achieved macro precision and recall of 99.72%. The AUC was 0.9999, showing outstanding class separability. Fold 4 yielded the best validation accuracy of 99.95%, with a training accuracy of 99.92%. Both macro precision and recall reached 99.95%, and the AUC peaked at 1.0000, signifying perfect performance in that fold. Fold 5 had the lowest validation loss of 0.0027, while achieving validation accuracy of 99.95% and training accuracy of 99.87% shown in figure 7. The overall accuracy is presented in figure 8 and overall loss for all folds given in figure 9. The precision, recall, and AUC scores were again 99.95% and 1.0000, respectively as figure 10.

The aggregate performance across all five folds is summarized below:

- Average Best Training Accuracy: 99.21%
- Average Best Training Loss: 0.0279
- Average Best Validation Accuracy: 99.07%
- Average Best Validation Loss: 0.0434

These results reflect the consistency and effectiveness of the modified VGG19 architecture in learning discriminative features from dermoscopic images for classifying various types of skin cancer.

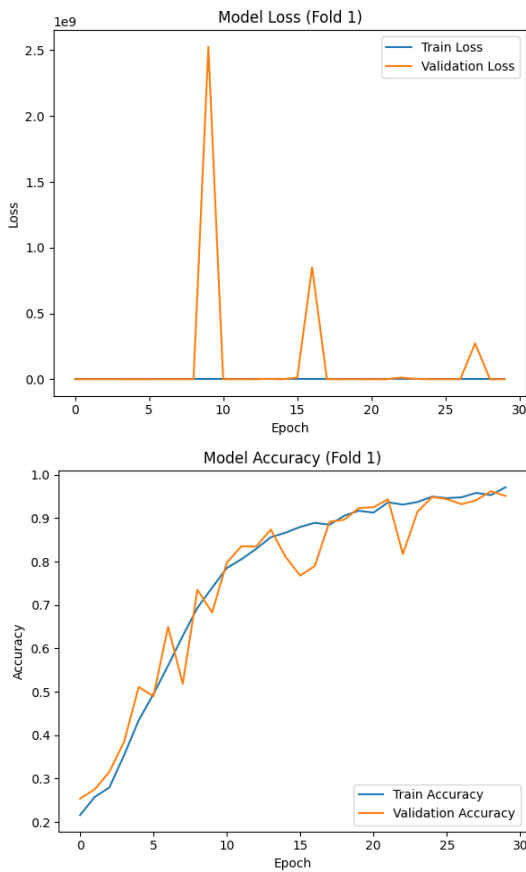


Fig. 6. Modified VGG19 model Accuracy and Loss on Fold 1.

The highest validation accuracy was observed in Fold 4 (99.95%), indicating the model’s remarkable ability to generalize across data. The lowest validation loss was noted in Fold 5 (0.0027), signifying a minimal error rate during prediction. The AUC scores across all folds ranged from 0.9960 to 1.0000, reflecting the model’s excellent capability in distinguishing between multiple skin cancer classes.

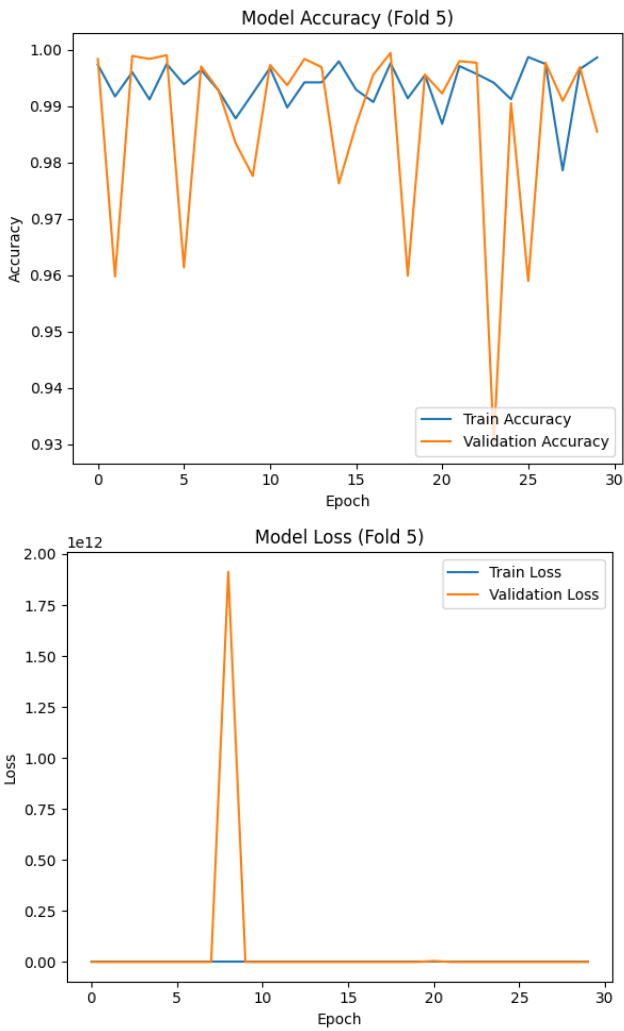


Fig. 7. Modified VGG19 model Accuracy and Loss on Fold 5.

Compared to traditional models or unmodified CNNs, the enhanced performance of the proposed Modified VGG19 highlights the significance of architecture tuning and fine-tuning pre-trained models for domain-specific applications such as skin cancer detection. These results establish the potential of deep learning models in assisting dermatologists with fast and accurate diagnosis, reducing the risk of manual error and improving early cancer detection.

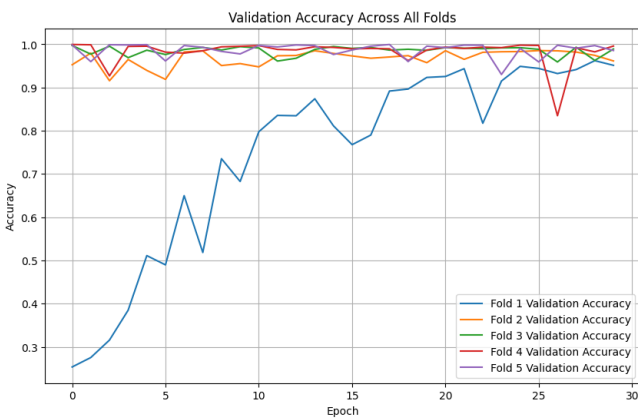


Fig. 8. Modified VGG19 model Accuracy graph across all Folds.

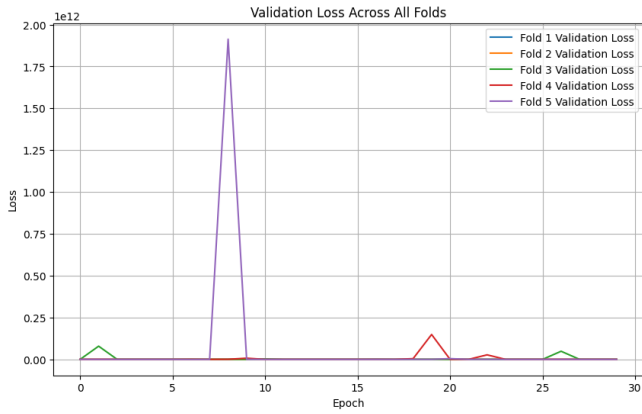


Fig. 9. Modified VGG19 model loss graph plot across all Folds.

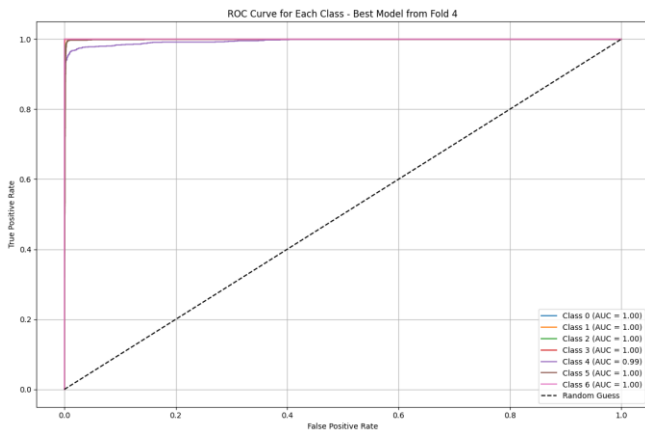


Fig. 10. Modified VGG19 model ROC Curve graph across all Folds.

To further evaluate the performance of the proposed Modified VGG19 model, a confusion matrix and corresponding classification report were generated based on the aggregated predictions across all classes given in figure 11 and Table 2. The confusion matrix provides a detailed account of how well the model performs on each class individually, highlighting its ability to distinguish between various types of skin cancer lesions.

TABLE I. CLASSIFICATION REPORT OF MODIFIED VGG19 MODEL FOR ALL CLASSES

	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	1341
1	0.99	1.00	1.00	1341
2	0.97	1.00	1.00	1341
4	0.99	0.91	0.95	1341
5	0.96	1.00	0.98	1341
6	1.00	1.00	1.00	1341
accuracy			0.99	9387
macro avg	0.99	0.99	0.99	9387
weighted avg	0.99	0.99	0.99	9387

A complete series of experiments was performed on the HAM10000 dataset, where the model proposed here was tested by 5-fold cross-validation. The highest validation accuracy was 99.95% (on Fold 4), and the lowest validation loss encountered was 0.0027 (on Fold 5). On average, the model obtained 99.07% validation accuracy, 0.0434 validation loss, and virtually perfect macro precision, recall, and F1-scores of 0.99. Against other prevailing methodologies such as CNN, YOLO, ResNet, and DODL Net, the Modified VGG19 model came out on top, scoring the highest collective classification accuracy of 99.07%. These findings attest to the architectural changes and training protocols that were employed in this study having greatly enhanced the model's capacity to identify and classify skin cancer, thus rendering it an effective medical image analysis and decision support tool for dermatologists.

Even though the suggested model had excellent performance, there are still a few areas in which future work can be focused on improving the effectiveness and applicability of the system in real clinical environments. Future research can use larger and more heterogeneous datasets, including scans of various ethnicities, age groups, and geographical locations, to make the model more generalizable and decrease dataset bias. Subsequent work can incorporate explainable AI (XAI) methods, e.g., Grad-CAM or LIME, to give visual justifications for predictions. This would enhance the confidence of medical professionals by indicating which parts of the lesion had the highest contribution to the model's prediction. Ensemble of dermoscopic images and patient metadata (e.g., gender, age, history of lesions) via multi-modal learning could also better classify and provide personalized diagnostic information.

REFERENCES

- [1] Gery P Guy Jr, Cheryl C Thomas, Trevor Thompson, Meg Watson, Greta M Massetti, and Lisa C Richardson. Vital signs: melanoma incidence and mortality trends and projections—United states, 1982–2030. *MMWR. Morbidity and mortality weekly report*, 64 (21):591, 2015.
- [2] Gery P Guy Jr, Steven R Machlin, Donatus U Ekwueme, and K Robin Yabroff. Prevalence and costs of skin cancer treatment in the us, 2002– 2006 and 2007– 2011. *American journal of preventive medicine*, 48 (2):183–187, 2015.
- [3] Robert S Stern. Prevalence of a history of skin cancer in 2007: results of an incidence-based model. *Archives of dermatology*, 146 (3):279–282, 2010.
- [4] Howard W Rogers, Martin A Weinstock, Steven R Feldman, and Brett M Coldiron. Incidence estimate of nonmelanoma skin cancer (keratinocyte carcinomas) in the us population, 2012. *JAMA dermatology*, 151 (10): 1081–1086, 2015.
- [5] <https://tinyurl.com/39sj38eb>. Accessed Apr 2022.
- [6] <https://tinyurl.com/yfb73knk>. Accessed Apr 2022.
- [7] Rebecca L Siegel, Kimberly D Miller, Hannah E Fuchs, and Ahmedin Jemal. *Cancer statistics, 2022*. CA: a cancer journal for clinicians, 2022.
- [8] Harold Kittler, H Pehamberger, K Wolff, and MJTIO Binder. Diagnostic accuracy of dermoscopy. *The lancet oncology*, 3 (3):159–165, 2002.
- [9] Ashfaq A Marghoob, Lucinda D Swindle, Claudia ZM Moricz, Fitzgerald A Sanchez Negron, Bill Slue, Allan C Halpern, and Alfred W Kopf. Instruments and new technologies for the in vivo diagnosis of melanoma. *Journal of the American Academy of Dermatology*, 49 (5): 777–797, 2003.
- [10] Afsaneh Jalalian, Syamsiah Mashohor, Rozi Mahmud, Babak Karasfi, M Iqbal B Saripan, and Abdul Rahman B Ramli. Foundation and methodologies in computer-aided diagnosis systems for breast cancer detection. *EXCLI journal*, 16: 113, 2017.
- [11] Haidi Fan, Fengying Xie, Yang Li, Zhiguo Jiang, and Jie Liu. Automatic segmentation of dermoscopy images using saliency combined with otsu threshold. *Computers in biology and medicine*, 85: 75–85, 2017.
- [12] Md Kamrul Hasan, Lavsén Dahal, Prasad N Samarakoon, Fakrul Islam Tushar, and Robert Martí. Dsnet: Automatic dermoscopic skin lesion segmentation. *Computers in Biology and Medicine*, 120: 103738, 2020.
- [13] Konstantin Korotkov and Rafael Garcia. Computerized analysis of pigmented skin lesions: a review. *Artificial intelligence in medicine*, 56 (2): 69–90, 2012.
- [14] Konstantina Kourou, Themis P Exarchos, Konstantinos P Exarchos, Michalis V Karamouzis, and Dimitrios I Fotiadis. Machine learning applications in cancer prognosis and prediction. *Computational and structural biotechnology journal*, 13: 8–17, 2015.
- [15] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *nature*, 521 (7553): 436–444, 2015.
- [16] Michel Fornaciari, Micael Carvalho, Flávia Vasques Bittencourt, Sandra Avila, and Eduardo Valle. Towards automated melanoma screening: Proper computer vision & reliable results. *arXiv preprint arXiv:1604.04024*, 2016.
- [17] P. Wighton, T. K. Lee, H. Lui, D. I. McLean, and M. S. Atkins. “Generalizing common tasks in automated skin lesion diagnosis,” *IEEE Trans. Inf. Technol. Biomed.*, vol. 15, no. 4, pp. 622–629, Jul. 2011.
- [18] J. Saeed and S. Zeebaree, “Skin lesion classification based on deep convolutional neural networks architectures,” *J. Appl. Sci. Technol. Trends*, vol. 2, no. 1, pp. 41–51, Mar. 2021.
- [19] Y. Li, A. Esteva, B. Kuprel, R. Novoa, J. Ko, and S. Thrun, “Skin cancer detection and tracking using data synthesis and deep learning,” 2016, *arXiv:1612.01074*.
- [20] U. Jamil, M. U. Akram, S. Khalid, S. Abbas, and K. Saleem, “Computer based melanocytic and nevus image enhancement and segmentation,” *BioMed Res. Int.*, vol. 2016, pp. 1–13, Jan. 2016.
- [21] V. Badrinarayanan, A. Kendall, and R. Cipolla, “SegNet: A deep convolutional encoder–decoder architecture for image segmentation,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 12, pp. 2481–2495, Dec. 2017.
- [22] K. M. Hosny, M. A. Kassem, and M. M. Foad, “Skin cancer classification using deep learning and transfer learning,” in *Proc. 9th Cairo Int. Biomed. Eng. Conf. (CIBEC)*, Dec. 2018, pp. 90–93.
- [23] A. Javaid, M. Sadiq, and F. Akram, “Skin cancer classification using image processing and machine learning,” in *Proc. Int. Bhurban Conf. Appl. Sci. Technol. (IBCAST)*, Jan. 2021, pp. 439–444.
- [24] R. Ashraf, I. Kiran, T. Mahmood, A. U. R. Butt, N. Razzaq, and Z. Farooq, “An efficient technique for skin cancer classification using deep learning,” in *Proc. IEEE 23rd Int. Multitopic Conf. (INMIC)*, Nov. 2020, pp. 1–5.
- [25] M. Uckuner and H. Erol, “A new deep learning model for skin cancer classification,” in *Proc. 6th Int. Conf. Comput. Sci. Eng. (UBMK)*, Sep. 2021, pp. 27–31.
- [26] Y. Filali, H. E. Khoukhi, M. A. Sabri, and A. Aarab, “Analysis and classification of skin cancer based on deep learning approach,” in *Proc. Int. Conf. Intell. Syst. Comput. Vis. (ISCV)*, May 2022, pp. 1–6.

- [27] Hoefler T, Alistarh D, Ben-Nun T et al (2021) Sparsity in deep learning: pruning and growth for efficient inference and training in neural networks. *J Mach Learn Res* 22(241):1–124. <https://doi.org/10.1145/3578356.3592583>
- [28] Co, skun M, YILDIRIM Ö, Ay, segül U et al (2017) An overview of popular deep learning methods. *Eur J Techn (EJT)* 7(2):165–176.
- [29] Wu H, Gu X (2015) Towards dropout training for convolutional neural networks. *Neural Netw* 71:1–10. <https://doi.org/10.1016/j.neunet.2015.07.007>
- [30] P. Tschandl, C. Rosendahl, and H. Kittler, “The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions,” *Sci. Data*, vol. 5, no. 1, pp. 1–9, Aug. 2018.
- [31] <https://www.kaggle.com/datasets/kmader/skin-cancer-mnist-ham10000>.
- [32] M. Khalaf, B.N. Dhannoon, Skin Lesion Segmentation based on U-Shaped Network, *Karbala Int J Mod Sci* 8 (3) (2022) 493–502.
- [33] R.R. Subramanian, D. Achuth, P.S. Kumar, K.N. kumar Reddy, S. Amara, and A.S. Chowdary, Skin cancer classification using Convolutional neural networks, in: 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence) IEEE, 2021, pp. 13-19.
- [34] H.M. Ünver, E. Ayan, Skin lesion segmentation in dermoscopic images with combination of YOLO and grabcut algorithm, *Diagnostics* 9 (3) (2019) 72, <https://doi.org/10.3390/diagnostics9030072>.
- [35] R. Garg, S. Maheshwari, A. Shukla, Decision support system for detection and classification of skin cancer using CNN, in: *Innovations in Computational Intelligence and Computer Vision: Proceedings of ICICV 2020*, Springer, Singapore, 2021, pp. 578-586.
- [36] Gomathi, E., et al. "Skin cancer detection using dual optimization based deep learning network." *Biomedical Signal Processing and Control* 84 (2023): 104968.