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Using Dermoscopic images and texture feature for Skin Cancer Detection

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Abstract

Deep learning has shown considerable promise for detecting skin cancer, particularly in dermoscopic pictures. In this study, a two-stage classification strategy has been created to improve diagnosis accuracy using the PH2 and ISIC 2019 datasets. First, the transfer learning with VGG19 and EfficientNet has been employed to extract deep features from images. These data were then integrated with 34 texture-based features and fed into a CNN, which enabled the model to identify between benign and malignant instances with 99.33% validation accuracy. For images determined as malignant, a second step was taken to determine the precise type of skin cancer among four groups. We used DenseNet121 for feature extraction, combined its deep features with texture descriptors, then put them through another CNN. This model achieved 91.20% validation accuracy. The findings demonstrate the efficacy of combining transfer learning and texture analysis, presenting a viable strategy to accurate and automated skin cancer classification.

Keywords: Skin Cancer, Medical Imaging, Transfer Learning, Densenet121, VGG19, Efficientnet, feature extraction, Deep Learning

1 Introduction

Skin cancer is one of the most frequent cancers worldwide, impacting millions of people each year. It happens when aberrant skin cells grow uncontrollably, which is commonly caused by excessive exposure to ultraviolet (UV) radiation from the sunrays. Skin cancer is among the most serious types of cancer. It is generated by unrepaired deoxyribonucleic acid (DNA) in skin cells, which results in genetic abnormalities or mutations. Skin cancer tends to gradually expand over other body areas; therefore, it is more curable in the earliest stages, which is why it is best identified at an early stage [1]. Melanoma, the most serious kind, can spread quickly to other regions of the body if not treated. Other forms, such as basal cell carcinoma and squamous cell carcinoma, are less aggressive but can cause significant tissue damage if not treated promptly. According to American Cancer Society statistics, melanoma skin cancer accounts for only 1% of all cases, but it has a higher fatality rate [2]. Melanoma develops in melanocytes. It begins when healthy melanocytes proliferate out of control, resulting in a malignant tumor. It can affect any part of the human body. It commonly arises in places that are exposed to sunlight, such as the hands, face, neck, and lips. Melanoma malignancies are only curable if detected early; otherwise, they spread to other body parts and cause the victim's terrible death [3]. Early identification of skin cancer is critical because it improves the likelihood of successful therapy. When discovered early, most skin malignancies can be removed with few surgeries, lowering the risk of complications and increasing survival rates. However, if cancer is not detected early enough, it can enter deeper layers of the skin and spread to key organs, making treatment more difficult.In advanced stages, chemotherapy, immunotherapy, or radiation may be required, although these therapies are not always effective in curing the disease. Early detection of skin cancer allows patients to obtain earlier medical intervention, resulting in better results and even full recovery. This is why creating precise and efficient diagnostic tools, such as deep learning-based models, is critical for increasing early detection and saving lives. Convolutional Neural Networks (CNNs) have transformed medical image processing, allowing for automatic and extremely accurate illness detection. CNNs can analyze dermoscopic pictures to detect malignant and benign lesions in the early stages of skin cancer. Transfer learning, which uses pre-trained models such as VGG19, EfficientNet, and DenseNet121, improves CNN performance by using information from big datasets, resulting in better feature extraction even with limited medical pictures. This strategy accelerates training and improves accuracy, making early detection more accessible and trustworthy. Early identification using CNN-based models is crucial because it enables timely medical intervention, lowering mortality rates and boosting treatment success. These models help dermatologists make faster, more accurate diagnosis by discriminating between malignant and benign lesions and identifying cancer subtypes. This can be especially useful in areas with limited access to expert healthcare providers. However, CNNs must be thoroughly trained to avoid any flaws. Poorly trained models may misclassify lesions, resulting in false positives that generate unneeded concern or false negatives that postpone treatment. Biases in training data can significantly decrease generalization, rendering the model incorrect for different skin tones and lesion types. When properly trained, CNNs combined with transfer learning can play a critical role in early skin cancer detection, increasing survival rates and boosting healthcare accessibility worldwide.

2 Literature Review

Meswal et al. [4] developed a weighted ensemble deep learning model for melanoma classification that was used to classify skin cancer using ISIC (International Skin Image Collection) dataset. The proposed model used an ensemble of seven deep learning models and achieved an accuracy of 85.54%. Maryam Tahir et al. [5] developed a multiclassification approach for diagnosing four forms of skin cancer: melanoma (MEL), melanocytic nevi (MN), basal cell carcinoma (BCC), and squamous cell carcinoma. They created a deep learning model called $DSCC_Net$ that is built on a convolutional neural network and tested it on three publicly available datasets: ISIC 2020, HAM 10000, and DermIS. In identifying the four separate forms of skin cancer disorders, they were able to get an AUC score of 99.43%, as well as 94.17% accuracy, 93.76% recall, 94.28% precision, and a 93.93% F1 score. ResNet-152, Vgg-19, MobileNet, and Vgg-16, as well as EfficientNet-B0 and Inception-V3, with accuracies of 89.68%, 92.51%, 91.46%, 89.12%, 89.46%, and 91.82%. The image input size was 150×150, and they used the Synthetic Minority Oversampling technique (SMOTE) to ensure that photos were evenly dispersed and that no one type of image was overfitted. They applied their model to six different baseline models to assess its performance against these baseline models and discovered that it outperformed them. The only issue was that the model is best suited for people with fair skin, as people with dark skin were not included in the dataset. The files lacked images of people with dark skin. In [6], Marriam Nawaz et al. investigated skin cancer detection using an RCNN model, which is a Region-based Convolutional Neural Network that is quicker than classic CNN, and they also used a fuzzy k-means clustering (FKM) model to classify it. They worked with three standard datasets: ISBI-2016, ISIC-2017, and PH2. Before training the model with their dataset, they first pre-processed the photos by reducing noise and illumination problems, allowing the model to capture the characteristics more easily and generalize effectively. The results outperformed the state-of-the-art models, with average accuracy of 95.40, 93.1, and 95.6% on the ISBI-2016, ISIC-2017, and PH2, respectively. Vipin Venugopal et al. [7] investigated skin cancer detection using EfficientNet, which easily outperformed state-of-the-art CNN models, and discovered that most of the models were utilized for binary classification, that is, determining whether it was melanoma or benign. To address this, they employed a layered architecture of efficientne-b4 and efficientnetv2-m models. They combined three datasets: ISIC 2020, ISIC 2019, and ISIC 2018. They used a variety of techniques to improve the model's efficiency and accuracy, including transfer learning and various types of image augmentation, which can help the model adapt to changes in images, and with transfer learning, they can extract features from that model to specifically design it for their desired outcome. They employed an image size of 224x224 and ran the model for 16 epochs, achieving a validation accuracy of 88.19% for EfficientNet-B4 and 90.19% for EfficientNetV2-M. The major drawback of this study was that it consisted of more benign images than malignant images, so the model may be a little biased towards the image being benign. The future scope of this study is to use GANs to create more malignant images and then test the performance of the DNN model. S.M. Alizadeh et al. [8] used a convolutional neural network and texture features to detect skin cancer in dermoscopic images. They employed the PH2, ISIC-2016, and ISIC-2019 datasets for their study and used two forms of CNNs. One is the standard CNN, while the other is the VGG-19, a complicated pretrained model trained on the imagenet dataset. They also employed several pre-processing methods to remove the hair from the dermoscopic images, including an algorithm dubbed DullRazor, which removes superfluous hair from the image. They also exploited texture features, which provide information on the order of colours and intensities in a specific area of a dermoscopy image. In this case, they used LBP and Haralick Features. The model's accuracy for each dataset is as follows: 85.2% for ISIC 2016, 96.7% for ISIC 2019, and 97.5% for the PH2 dataset. J.S. M et al. [9] trained their model utilizing ISIC 2019 and ISIC 2020 datasets, as well as transfer learning with the EfficientNet architecture, which can learn complicated and fine-grained patterns from images. The dataset consisted of photos of various resolutions and was very imbalanced, which might have affected the score if not handled appropriately. To address this, they employed two separate transfer learning techniques: feature extractor and fine tuning. The model's performance was evaluated using the AUC-ROC curve and received a score of 0.9681. A ranger optimizer also been used in their work, which reduces hyper-parameter adjustment to get cutting-edge outcomes. This was a binary classification study, which solely indicated whether the picture was malignant or non-malignant. Overall, the model efficiency has been improvised by 6% when compared with the state-of-the-art models. Flavia Grignaffini et al. [10] analyzed several studies on skin cancer detection and selected papers from 2012-2022. In their investigation, it was discovered that the majority of machine learning models employed SVM for classification, with 42.86% of papers containing an SVM model, and that pre-trained CNN models such as EfficientNet, ResNet, and others were the most commonly used in deep learning. Almost 70% of the publications utilizing DL models employed pre-trained CNN models, with the remainder using unique models. They found that all of the research papers they reviewed were focused at assisting physicians and making it simpler to detect skin cancer in its early stages, but not at replacing physicians because if it is not detected correctly, it may be difficult to cure. Ahmad Naeem et al. [11] created a unique model dubbed SCDNet, which is a hybrid of VGG-16 and CNN, and then compared it against four state-of-the-art models, using the ISIC 2019 dataset. The model achieved an accuracy of 96.91, which outperformed all four cutting-edge models employed in this comparison. They used the ISIC 2019 dataset, which consisted of many images of various skin cancers. They only selected four types of skin cancer and discarded the remaining samples. They divided their data into training, testing, and validation sets in the following ratio: 70%: 20%: 10%. The study's only shortcoming was that it worked well for fair-skinned people but was insufficient for dark-skinned people because the databases did not include dark-skinned people images. R. O. Ogundokun et al. [12] combined MobileNetV2 and Xception models to develop a model capable of detecting skin cancer more accurately, and used a publicly available skin cancer dataset for their study. Because they didn't have enough data to train a deep learning model, the data was enhanced by rotating and translating, as DL models operate best on large datasets. The transfer learning because these models have already been trained on massive datasets, saving a lot of time and resources. They chose five TL models for their study. There model achieved an accuracy of 97.56%, which was greater than the pre-trained models. The study's limitation was that it was primarily reliant on pre-trained models and lacked image quantity, with only 204 photographs with cancer and 204 without cancer. S. Bechelli et al. [13] conducted research utilizing both machine learning and deep learning models, comparing their effectiveness in detecting skin cancer. The study used Kaggle's skin cancer dataset and machine learning models such as linear regression, K-nearest neighbours, linear discriminant analysis, decision tree classifier, and Gaussian naïve bayes. For deep learning, they selected three pre-trained models: Xception, VGG16, and ResNet50. They were able to achieve an accuracy of 75% for machine learning with ensemble techniques but were unable to exceed it, whereas deep learning models achieved an accuracy of 88%. O. Attallah et al. [14] wanted to create a model that could be used for CAD or computer-aided diagnosis, so they combined four CNNs with different layers and architectures to find the most important features, and as a result, they were able to diagnose whether it was malignant or benign. For this study, HAM10000 datasets were employed, and they achieved an accuracy of 97.2% for malignant and 96.5% for benign. The Skin-CAD model is an advanced explainable artificial intelligence (XAI) model, whereas traditional models are mysterious and unpredictable, sometimes known as black box approaches. They initially determined whether the image was malignant or benign, and if it was discovered to be malignant, it was classed as one of seven forms of skin cancer. In their research, they got deep CNN features such as pooling and fully connected layers, which were then filtered down using PCA to reduce computation burden and time. P. Narmatha et al. [15] used dermoscopic images to create a deep Siamese domain adaption convolutional neural network, or DSDACNN, in which the input images were first pre-processed to remove noise and any lighting issues that could change the appearance of the image, and the output was passed to the actual model as an input. The honey badger algorithm was also used to optimize the weight parameters, resulting in a 24-35% improvement in computational time and an F1 score that was 15.5-25.5% higher than existing methods such as SKD-FKMC, SKD-HNHF, etc. They chose this method because existing deep learning models had two issues: high computational cost and model overfitting. To address these two issues, DSDACNN and honey badger algorithm was used to reduce the computational time required to train a model. The ISBI-2016 dataset was utilized for experimentation. Ahmad Naeem et al. [16] used deep learning models with handmade feature extraction methods to test the model against four baseline models and six state-of-the-art (SOTA) models, and used ISIC 2019 dataset. F1 score of 98.10%, a recall of 97.89%, a precision of 98.31%, and an accuracy of 97.81% was achieved by models to classify skin cancers into eight types and used techniques such as SMOTE to compensate for an unbalanced dataset that had more images of one type of skin lesion than the other. By using SMOTE, they were able to ensure that the model was trained with an equal set of images of each type of lesion so that it was not biased towards the image with the most quantity. The future scope of this research was to use federated learning to improve skin cancer classification accuracy even further. In the study conducted by A. Dascalu et al. [17] used two CNNs, the first CNN's role was to find out the malignancy of the image while the second CNN used a technique called sonification after which the CNNs were combined into a single CNN to generate the output. It was found that the dermoscopic images had an AUC score of 0.91 while the AUC score of smartphone images was 0.82.

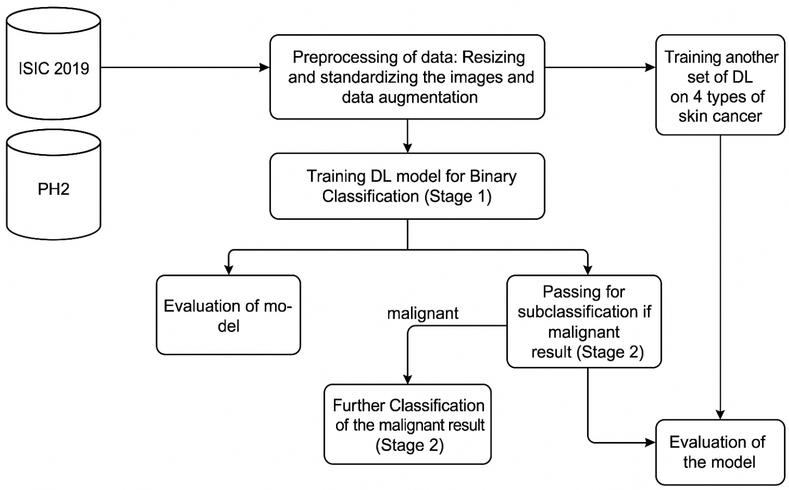

Fig. 1: Proposed Methodology

3 Research Methodology

This study proposed a two-step classification strategy in which two separate CNN networks were utilized to determine whether the dermoscopic images were malignant or benign, and if it was malignant, it could be sub-classified into the type of skin cancer.

3.1 Analysis of the Data

In this investigation, two publicly available medical imaging datasets were utilized to train and evaluate the model: the PH2 skin cancer dataset [18] and the ISIC-2019 dataset. The ISIC 2019 dataset comprises of 3 different datasets and they are as follows: $BCN_2$0000 Dataset [19], HAM10000 Dataset [20] and MSK Dataset [21]. These databases contained skin cancer images, with PH2 containing malignant and benign images and ISIC-2019 containing various types of skin cancer images. Only four of the eight sub-classes of skin cancer were used in this investigation, which are as follows: Benign Keratosis (BKL), Melanoma (MEL), Squamous Cell Carcinoma (SCC), and Vascular Lesion (VASC). The PH2 dataset had 200 photos that were sorted into two categories: 40 with skin cancer and 160 without skin cancer. During the preparation phase, the image was scaled and normalized, and the data was expanded to include 1000 images for each class. The ISIC-2019 photos totaled 25,331 images, with 14,204 utilized to train the model and 6,088 used to test the model's performance. During the preprocessing phase, all of the photos were scaled, normalized, and relocated to the appropriate skin cancer type folder. The PH2 dataset was split as 70-15-15 where 70% of the data was used for training,15% for validation and the remaining 15% to test the model. The ISIC-2019 data was split using the same metrics as PH2 meaning it was also split in the ratio 70-15-15.

In this study, a two-step classification method was applied, in which the CNN first took the image and its texture features using GLCM and LBP, and then transmitted them to the network for binary classification to determine if the image is malignant or benign. If the image is malignant, it is passed via another CNN, which oversees sub-classifying the malignant images. GLCM features are used to analyze how pixel brightness varies with direction and distance while LBP texture For the first step of the two-step classification, two transfer learning models were trained: VGG-19 and EfficientNet on the image's dataset and the transfer learning models were optimized by unfreezing the last 10 layers of them so the model could learn from the image dataset. Their features were extracted from the last 3 layers and were then concatenated together along with texture features, and a new CNN was created in which these extracted features were used in conjunction with texture features from GLCM and LBP, for a total of 34 texture features per image, 24 from GLCM and 10 from LBP. The final CNN ran for 7 epochs and had a validation accuracy of 99.33%. Densenet was utilized for transfer learning in the second step of this classification, with the ISIC-2019 dataset as its training set. In this case, the Densenet model was trained on the dataset and last 7 layers of the model were trained for optimizing the weights, and then the features were extracted from the model and sent through a new CNN coupled with the image's texture features, which would considerably aid in categorizing the image and lesion type. This CNN was used to only classify four forms of skin cancer, and a dropout layer was employed and set to 0.5 so that the model would not overfit, and L2 regularization of 0.0001 was implemented to prevent the model from getting overfitted.

4 Model Architecture

A Convolutional Neural Network (CNN) is a deep learning model designed primarily for image processing, making it extremely useful in skin cancer diagnosis. CNNs, unlike traditional machine learning models that need manual feature extraction, automatically learn spatial hierarchies of features such as edges, textures, and patterns using convolutional layers. These layers employ filters to identify relevant structures in the input image, followed by pooling layers to reduce dimensionality while maintaining critical information. Fully linked layers then identify the images, while activation functions like ReLU leverage nonlinearity to improve learning. CNNs are widely used in dermatology because they excel in distinguishing between diverse skin lesions, including melanoma, basal cell carcinoma, and benign lesions, by detecting minute differences in texture, color, and shape. Transfer learning uses pre-trained deep learning models like VGG19, EfficientNet and DenseNet121 which have previously learned useful image properties from large datasets like ImageNet. Instead of training a CNN from scratch, researchers can use these models to extract features or fine-tune them for specific datasets, such as ISIC 2019, to classify skin lesions. This strategy reduces training time while enhancing performance, even with limited data.

5 Results and Analysis

The binary classification approach demonstrated a high level of accuracy in identifying skin cancer. The model obtained 99.33% test accuracy and correctly identified whether the photos were malignant or not. For this PH2 dataset was used to train the model and the images were of size 224x224 and 3 color channel and the data was also augmented to increase the number of images and to generalize the model for unseen data. The augmented images were flipped, rotated, zoomed brightness were altered and then the new images were saved in the dataset directory. The model was first trained using VGG-19 and then trained again using EfficientNet and both were trained, and their last 10 layers were allowed to fine tune by letting them train on the dataset. The transfer learning models were both trained for 10 epochs and then the features were extracted and were concatenated with texture features and passed as an input in the final CNN which took image and image texture as input and then processed them. Figure 2 depicts the loss curve of the CNN created with VGG19 and efficientnet, as well as texture features, and from the figure it could be seen that the train and validation loss have plateaued. Figure 3 shows the accuracy curve of the sub-classification CNN, which was trained for ten epochs. As we can see, the model attained a validation accuracy of 91.20% and a training accuracy of 98.26%. The model achieved good accuracy but had a high rate of validation loss, even after employing dropout layers and L2 regularization. The validation loss was close to 33%, which was greatly decreased after the addition of L2 regularization but could not be reduced further.

If the image was categorized as benign then the process would end there but if the image was categorized as malignant, it was passed through another CNN where it was further sub-classified and identified the type of skin cancer. For this, four skin cancer types were evaluated, and to train this model, the ISIC-2019 dataset was utilized. The CNN used DenseNet121 features, and texture

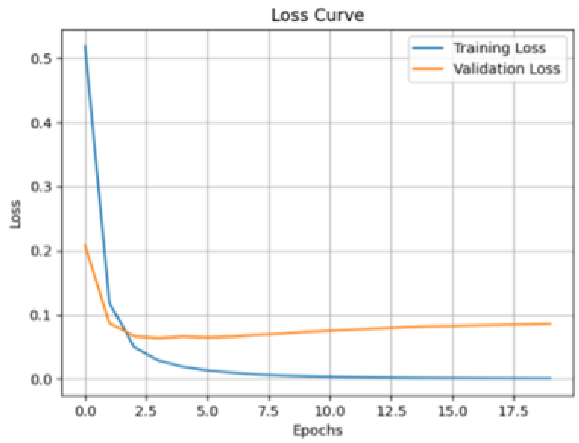

Fig. 2: Loss curve of CNN

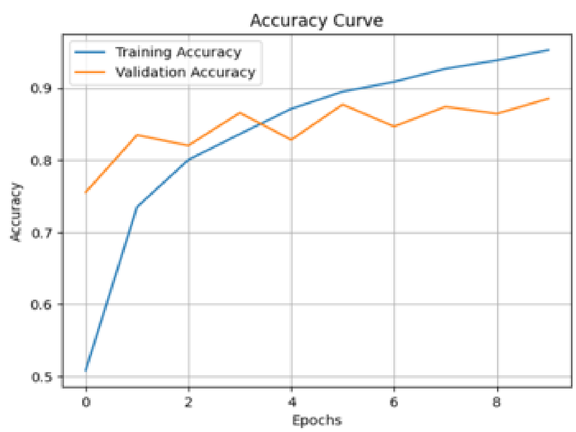

Fig. 3: Accuracy Curve of sub-classification CNN

features were generated from the input images and a total of 14 texture features were used per image and were fed into the model as an input along with the image. The model achieved an accuracy of 98.26%. The model successfully classified the four classes and achieved a validation accuracy of 91.20%. Dropout and regularization layers were added in the CNN as well to prevent the model from overfitting and a learning rate was also set so that the model wouldn't be overfit on the training dataset too fast.

Table 1: Performance Comparison of Binary CNN and Subclass CNN

Metric	**Binary CNN (%)**	**Subclass CNN (%)**
Precision	99.00	87.22
Recall	99.00	87.28
F1-Score	99.00	87.22
Accuracy	99.00	87.11

Table 1 shows the results of both the CNNs for binary classification and subclassification of skin cancer, and it can be seen that the binary CNN performed very well, achieving near-perfect results with an F1 score and precision of 100%, implying that the binary classification CNN is working well,

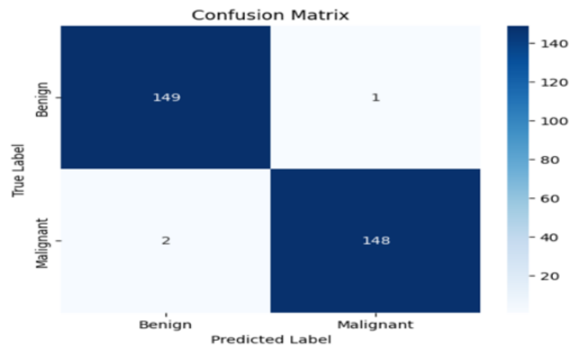

Fig. 4: Confusion Matrix of 1st CNN

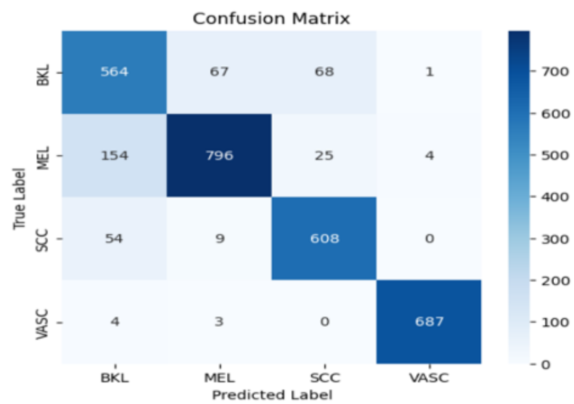

Fig. 5: Confusion matrix of 2nd CNN

whereas the subclassification CNN performed well but not as well as the binary classification CNN but it still managed to achieve 91% accuracy and had a precision and F1 score of 91.20% meaning the model was able to correctly predict the actual skin cancer class 91% of the time. Although the model could be fine-tuned to increase the result even more and by incorporating more transfer learning models to extract features which could significantly increase the performance of the model. Figures 4 and 5 demonstrate the confusion matrix for the binary classification and subclassification networks, respectively. The results showed that the binary classification was able to correctly identify the classes without issue, however the subclassification network had higher misclassification and false positives and negatives in comparison to binary classification model. It appears that the model struggled with the ISIC 2019 dataset and was unable to classify the skin cancer classes as readily as the PH2 dataset's binary categorization. The 2nd CNN managed to get a precision, recall and F1-score of 99% for VASC and performed excellently in identifying VASC skin cancer. The worst performance was seen from BKL skin cancer which had and very poor recall and F1-score. The sigmoid function converts an input into a value between 0 and 1, and it is most typically employed in binary classification problems, therefore it would perform best in this scenario when the model was supposed to predict whether the image was cancerous or benign. The function follows an S-shaped curve, which means that tiny inputs map close to 0, big inputs map close to 1, and values near 0 are more sensitive to change. Sigmoid is still commonly employed in logistic regression and as the final activation function in binary classification tasks that require output probabilities.

6 Conclusion

In this study, we used a CNN to classify skin cancer by using integrating image data and texture cues. Furthermore, features derived from transfer learning models (VGG19, EfficientNet, and DenseNet) considerably improved model performance. The study used two datasets: PH2 for binary classification and ISIC-2019 for subclassification of skin cancers. Our binary classification model performed flawlessly, with 99% testing accuracy, F1 score of 0.99, and precision of 0.99. The subclassification model, which used DenseNet features, achieved a training accuracy of 95.65% and an F1 score and accuracy of 87.22% on the validation dataset. The model managed to identify 3 of the skin cancer types out of the 4 which were used in this study and out of all of them the only one performed very poorly in-comparison to the other skin cancer types and that was BKL while the others performed very well except BKL. However, its effectiveness on previously unreported test data implies that there is still opportunity for improvement in identifying certain types of skin cancer. These data suggest that, while the model is highly effective in detecting skin cancer, its subclassification accuracy requires further improvement. Future research could look at more advanced architectures, improved texture feature integration, and unique deep learning algorithms to improve subclassification accuracy and the model's capacity to detect distinct types of skin cancer with higher precision. For future studies transformers can be used to see how well they perform and whether they are feasible or not and using techniques like sonification which converts the visual representation into non-speech audio signals which can help identify hidden patterns in the cancer cell images and may help improve the metrics of the model while making it more robust.

Declarations

- The authors received no specific funding for this study.
- The authors declare that they have no conflicts of interest to report regarding the present study.
- No Human subject or animals are involved in the research.
- All authors have mutually consented to participate.
- All the authors have consented the Journal to publish this paper.
- Authors declare that all the data being used in the design and production cum layout of the manuscript is declared in the manuscript.

References

[1] Dildar, M., *et al.*: Skin cancer detection: a review using deep learning techniques. International journal of environmental research and public health **18**(10), 5479 (2021)

[2] American Cancer Society: Key Statistics for Melanoma Skin Cancer. https://www.cancer.org/content/dam/CRC/PDF/Public/8823.00.pdf. Accessed on 8 February 2021 (2021)

[3] Khan, M.Q., *et al.*: Classification of melanoma and nevus in digital images for diagnosis of skin cancer. IEEE Access **7**, 90132–90144 (2019)

[4] Meswal, H., *et al.*: A weighted ensemble transfer learning approach for melanoma classification from skin lesion images. Multimedia Tools and Applications **83**(11), 33615–33637 (2024)

[5] Tahir, M., *et al.*: Dscc_net: multi-classification deep learning models for diagnosing of skin cancer using dermoscopic images. Cancers **15**(7), 2179 (2023)

[6] Nawaz, M., *et al.*: Skin cancer detection from dermoscopic images using deep learning and fuzzy k-means clustering. Microscopy Research and Technique **85**(1), 339–351 (2021) https://doi.org/10.1002/jemt.23908

[7] Venugopal, V., *et al.*: A deep neural network using modified efficientnet for skin cancer detection in dermoscopic images. Decision Analytics Journal **8**, 100278 (2023)

[8] Alizadeh, S.M., Mahloojifar, A.: Automatic skin cancer detection in dermoscopy images by combining convolutional neural networks and texture features. International Journal of Imaging Systems and Technology **31**(2), 695–707 (2021)

[9] SM, J., *et al.*: Classification of skin cancer from dermoscopic images using deep neural network architectures. Multimedia Tools and Applications **82**(10), 15763–15778 (2023)

[10] Grignaffini, F., *et al.*: Machine learning approaches for skin cancer classification from dermoscopic images: A systematic review. Algorithms **15**(11), 438 (2022) https://doi.org/10.3390/a15110438

[11] Naeem, A., *et al.*: Scdnet: a deep learning-based framework for the multiclassification of skin cancer using dermoscopy images. Sensors **22**(15), 5652 (2022)

[12] Dascalu, A., et al.: Non-melanoma skin cancer diagnosis: a comparison between dermoscopic and smartphone images by unified visual and sonification deep learning algorithms. Journal of cancer research and clinical oncology, 1–9 (2022)

[13] Ogundokun, R.O., *et al.*: Enhancing skin cancer detection and classification in dermoscopic images through concatenated mobilenetv2 and xception models. Bioengineering **10**(8), 979 (2023) https://doi.org/10.3390/bioengineering10080979

[14] Bechelli, S., Delhommelle, J.: Machine learning and deep learning algorithms for skin cancer classification from dermoscopic images. Bioengineering **9**(3), 97 (2022)

[15] Attallah, O.: Skin-cad: Explainable deep learning classification of skin cancer from dermoscopic images by feature selection of dual high-level cnns features and transfer learning. Computers in Biology and Medicine **178**, 108798 (2024)

[16] Narmatha, P., *et al.*: Skin cancer detection from dermoscopic images using deep siamese domain adaptation convolutional neural network optimized with honey badger algorithm. Biomedical Signal Processing and Control **86**, 105264 (2023)

[17] Naeem, A., *et al.*: Snc_net: skin cancer detection by integrating handcrafted and deep learning-based features using dermoscopy images. Mathematics **12**(7), 1030 (2024)

[18] Mendonça, T., *et al.*: Ph 2-a dermoscopic image database for research and benchmarking. In: 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (2013). IEEE

[19] Tschandl, P., Rosendahl, C., Kittler, H.: The ham10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. Scientific data **5**(1), 1–9 (2018)

[20] Codella, N.C., *et al.*: Skin lesion analysis toward melanoma detection: A challenge at the 2017 international symposium on biomedical imaging (isbi), hosted by the international skin imaging collaboration (isic). In: 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018) (2018). IEEE

[21] Hernández-Pérez, C., *et al.*: Bcn20000: Dermoscopic lesions in the wild. Scientific data **11**(1), 641 (2024)