Melanoma Detection Using Convolutional Neural Network

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***Abstract*—Melanoma, a severe kind of skin cancer, requires early identification to enhance patient outcomes. This paper describes a unique approach to melanoma diagnosis that combines image processing techniques with deep learning methodologies. This paper provides a method for analyzing skin lesion photos that uses a mix of color, texture, and form factors, followed by classification using a convolutional neural network. Using a publicly accessible collection of skin lesion photos, this method obtained a 93% accuracy in differentiating between malignant and benign lesions. These positive findings suggest that this study approach has the potential to considerably benefit dermatologists in the early detection of melanoma, improving treatment outcomes and patient survival.**

***Keywords*—dermatology, melanoma, skin cancer, machine learning, Gaussian mixture model, backpropagation neural network, integrated development environment**

I. Introduction

Melanoma, a kind of skin cancer, develops when melanocytes, the skin's pigment-producing cells, start to grow uncontrolled. Cancer develops when the body's cells begin to proliferate uncontrollably, and these malignant cells can spread to other organs [1]. Although melanoma is far less prevalent than other forms of skin cancer, it is more hazardous since it has a high risk of spreading to other regions of the body if misdiagnosed and not treated. Melanomas can grow anywhere on the skin, although men and women are more likely to acquire them on their trunks (chest and backs). Other common places are the neck and face. Melanoma is less likely to develop in these typical sites in people with darkly pigmented skin, although it can still arise on the hands, feet, or beneath the nails. Melanoma can also form in the mouth, genitalia, anal region, and eyes, but this is less frequent [1].

Skin cancers are divided into three types: basal cell carcinoma, squamous cell carcinoma, and melanoma. Traditionally, clinicians utilize a biopsy to diagnose skin cancer. However, with improvements in Artificial Intelligence (AI), it is possible to design a simpler approach, such as a smartphone application, to detect skin cancer more easily. Melanoma, the deadliest kind of skin cancer, can be both benign and malignant. Previous study by [2] used a Convolutional Neural Network (CNN) for melanoma detection but struggled to effectively categorize benign and malignant moles, with an 89.63% accuracy rate in identifying malignant moles.

Similarly, [3] had problems with erroneous predictions and finding skin lesions [4] used CNNs to discriminate between benign and malignant moles, with an accuracy of 81.89% on the validation set, which is insufficient for real-time applications.

Patients may experience discomfort and worry throughout the biopsy procedure for identifying skin cancer, which can take up to 2 to 3 weeks. Biopsies are tiny surgeries that cause localized pain for a few days. The major objective is to assist people get accurate and speedy skin diagnostics in a simple and cost-effective manner.

This study aims to diagnose melanoma by analyzing skin images using image processing and CNNs. Previous studies, such as [2], indicate a need for improved classification of benign and malignant moles. This research seeks to enhance this classification accuracy. Accurate differentiation between benign and malignant melanoma is crucial as the former is non-cancerous and slow-growing, while the latter is cancerous, aggressive, and potentially fatal. The process includes image acquisition, preprocessing, segmentation, and classification to determine if the melanoma is benign or malignant.

II. Related Work

Recent advances in technology have enabled us to identify cancer cells using CNN, Image processing. Despite these advancements, there are challenges yet need to be addressed. Previous studies have shown that there are limitations. In this section, we review existing research and methodologies related to the detection of melanoma skin cancer, particularly focusing on the technologies and advantages and limitation of each approach. The papers provided restrictions as well as some extremely important insights that could be used to develop the model.

According to [5] Gaussian Mixture Model (GMM) and Backpropagation Neural Network (BPN) have been explored in the context of melanoma detection. The equipment based on GMM and BPN has shown promise by demonstrating the capability to meet the demand for scheduled eradication of skin malignancy. This approach is designed for simplicity of operation and robust performance across various photographic situations. As [6] introduced a melanoma detection method based on the Faster-regional based convolutional neural network (RCNN) with fuzzy k-means clustering (FKM). Their presented method has a 0.90 in sensitivity whilst techniques like SFU-mial and CUMED has 0.915 and 0.911 respectively. Also their presented method has 0.971 in specificity whilst TMUteam and UiT-Seg has 0.987 and 0.974. Their work stands out for its ability to outperform state-of-the-art lesion detection approaches in terms of accuracy. Notably, this superior performance is achieved with a relatively shallow network architecture.

As [3] proposed InSiNet as a dedicated machine learning technique for melanoma detection. Their research involved extensive comparisons with various other machine learning

techniques and incorporated the use of multiple datasets. The method still has to be tested in huge datasets and .dicom format. Another issue is determining the location of skin lesions. There are few false predictions.

The results of their study provide valuable insights into the effectiveness of InSiNet in the context of skin cancer detection.

Recent study emphasizes the variety of approaches used in melanoma detection. For example, [7] compared the diagnosis accuracy of a deep learning convolutional neural network to dermatologists and discovered that the CNN performed similarly to human specialists in identifying melanoma using dermoscopic pictures. Similarly, [8] demonstrated that a deep CNN trained end-to-end using just photos and illness labels, with no feature extraction done manually, obtained performance equivalent to dermatologists.

Codella *et al.* [9] conducted a detailed examination of several machine learning algorithms used to identify melanoma and shown the potential of ensemble learning approaches to increase classification accuracy. Furthermore, [10] investigated the use of generative adversarial networks (GANs) to supplement training data for melanoma detection models, resulting in better performance via synthetic data creation.

According to [11], an extremely deep CNN for melanoma detection was developed, which used a fully convolutional residual network (FCRN) with 16 residual blocks for segmentation, resulting in better performance. The proposed strategy employed both SVM and softmax classifiers for classification. Their technique classified melanoma with 85.5% accuracy using clustering and 82.8% without clustering.

DeVries and Ramachandram [12] created a multi-scale CNN for skin cancer classification based on an Inception v3 deep neural network trained on the ImageNet dataset. The pre-trained network was fine-tuned utilizing both coarse and high-scale input lesion image frequency scales to capture broad ambient signals as well as lesions' form properties. The higher scale was also used to collect textual information on the lesion to distinguish it from other forms of skin lesions.

Mahbod *et al.* [13] created a skin lesion classification approach that used pre-trained deep CNNs such as AlexNet, ResNet-18, and VGG16 to extract detailed characteristics. These characteristics were utilized to train a multi-class classification approach, and the classifiers' results were combined for final classification. On the ISIC 2017 dataset, the suggested technique performed well with an area under the curve (AUC) of 97.55% for Seborrheic Keratosis (SK) and 83.83% for melanoma.

Mendes and Silva [14] introduced a deep CNN architecture based on a pre-trained ResNet-152 for classifying skin lesions into 12 distinct kinds. The suggested technique includes training the network with a dataset of 3797 lesion photos, followed by 29 iterations of augmentation utilizing scale and illumination conditions. The approach was very accurate in diagnosing hemangioma, pyogenic granuloma (PG), and Intraepithelial Carcinoma (IC) skin lesions, with an AUC value of 0.99.

Dorj *et al.* [15] suggested a technique that used a pre-trained deep CNN, AlexNet, for feature extraction and a coding SVM to classify four different types of skin lesion pictures. The method achieved high classification performance for squamous cell carcinoma (SCC), actinic keratosis (AK), and basal cell carcinoma (BCC), with the highest average sensitivity, accuracy, and efficiency ratings among the evaluated methods, at 95.1%, 98.9%, and 94.17%, respectively.

Furthermore, Esteva *et al.* [8] demonstrated the usefulness of a deep CNN trained end-to-end using just photos and illness labels, with performance equivalent to dermatologists. Their technique proved that CNNs can equal human competence in identifying melanoma using dermoscopic pictures. This study [9] conducted a detailed examination of several machine learning algorithms used to identify melanoma, highlighting the potential of ensemble learning approaches to increase classification accuracy. Their findings indicate that merging various models can result in more robust performance.

These studies demonstrate the substantial advances made in the field of melanoma detection utilizing deep learning and CNNs, while also highlighting areas for further study and development. The findings from these studies are critical for building more accurate and reliable melanoma detection algorithms.

III. Methodology

In this section, we outline the methodology employed in the development of the melanoma skin cancer detection system. The methodology encompasses data acquisition, model development, libraries and tools utilized, and the selection of Integrated Development Environments (IDEs) to facilitate the project.

A. Data Acquisition

To construct a robust melanoma skin cancer detection model, we obtained a comprehensive data set [16] from Kaggle. This data set comprises a total of 10,000 images, with 9,600 images designated for model training and 1,000 images for evaluation. The data set is organized into two primary folders, "train" and "test," each containing images representing both benign and malignant melanoma skin conditions. The selection of this data set was driven by its alignment with the specific requirements of this research. Further bolstering its suitability, Kaggle has conferred a usability grade of 7.5 on this data set, and it has been employed successfully in eight projects on the Kaggle platform.

B. Model Development

The development of the deep learning model was carried out using Python, a versatile programming language widely acclaimed in the domains of data science and machine learning due to its rich ecosystem of libraries and ease of use [17]. Essential libraries such as NumPy, Pandas, TensorFlow, Keras, Scikit-learn and Matplotlib played pivotal roles in facilitating data manipulation, analysis, and the construction of intricate Convolutional Neural Network (CNN) models [18–22]. Python's inherent cross-platform compatibility ensured seamless execution across diverse operating systems.

C. User Interface

The user interface (UI) was realized through a combination of front-end and back-end technologies. The front-end design was crafted using HTML5 and CSS [23,24]. The back-end functionality was implemented through a stack comprising Flask 2.2.3, Pillow 9.5.0, Keras 2.12.0, NumPy 1.23.5, in conjunction with PHP, JavaScript, and MySQL [17, 25–30], enabling seamless user interactions with the deep learning model.

D. IDE

For the development of the CNN-based model, we harnessed the capabilities of Google Colaboratory (Google Colab) as the preferred integrated development environment (IDE). This cloud-based platform not only facilitated the loading of the dataset but also ensured the smooth execution of the model [31]. Additionally, the collaborative features of Google Colab allowed for team members to work jointly, promoting efficiency and teamwork.

In tandem, we selected PyCharm as the IDE of choice for the creation of the internet application. The distinctive qualities of PyCharm, such as its powerful testing and debugging capabilities, cross-platform compatibility, seamless tool integration, intelligent coding tools, and vibrant community support environment, made it the best option for developing online applications [32]. These qualities were essential to the effective design and implementation of the online application for skin cancer screening.

E. Testing and Evaluation

For the purpose of training and evaluation, we adopted a conventional 80–20 split of the dataset, allocating 80% of the images for training the model and reserving the remaining 20% for testing. This division ensured a balanced representation of data for training and validation, facilitating a rigorous evaluation of the model's generalization capabilities.

The following metrics are taken into account in this study:

1) Precision $= \frac{TP}{(FP+TP)}$: How many estimates are accurate out of all the estimates
2) Recall $= \frac{TP}{(TP+FN)}$: How many true positive classes are accurately classified
3) F1 score $= \frac{2\times \text{Precision} \times \text{Recall}}{(\text{Precision}+\text{Recall})}$: The computation of the harmonic mean through recall and accuracy.
4) Accuracy $= \frac{(TP+TN)}{(\text{TP}+\text{FP}+\text{TN}+\text{FN})}$: Overall effectiveness of the classifier.

Table 1. Performance metrics of the model

Class	Precision	Recall	F1-Score	Support
0	0.95	0.93	0.94	500
1	0.91	0.94	0.93	389
Accuracy			0.93	889
Macro Avg	0.93	0.93	0.93	889
Weighted Avg	0.93	0.93	0.93	889

Table 1 presents the performance metrics, including precision, recall, F1-score, and accuracy, used to evaluate the classification model's effectiveness across different classes. The metrics provide insights into how well the model distinguishes between the two target classes.

- Precision: For class 0 (benign melanoma) and class 1 (malignant melanoma), the precision scores were 0.95 and 0.91, respectively. These scores indicate the proportion of true positive predictions among all positive predictions.
- Recall: The recall scores for class 0 and class 1 were 0.93 and 0.94, respectively. These scores represent the proportion of true positives correctly identified by the model relative to all actual positives.
- F1-score: For class 0 and class 1, the F1-scores were 0.94 and 0.93, respectively. The F1-score is the harmonic mean of precision and recall, providing a balanced measure of a model's accuracy.
- Support: The support values denote the number of instances for each class (0 and 1) in the test dataset.
- Accuracy: The overall accuracy of the model was 0.93, indicating the proportion of correctly classified instances among all instances in the test dataset.
- Macro Average: The macro average of precision, recall, and F1-score was 0.93, reflecting a balanced performance assessment across both classes.
- Weighted Average: The weighted average of precision, recall, and F1-score was 0.93, indicating an overall model performance score that considers class imbalances.

IV. Discussion

In this section, we interpret the results of our melanoma skin cancer detection model and discuss their implications. Additionally, we compare this model's performance to existing literature and benchmarks, shedding light on its effectiveness in the context of skin cancer detection.

A. Model Performance and Implications

The melanoma skin cancer detection model, built on a deep learning architecture using TensorFlow and Keras, has yielded promising results. With an overall accuracy of 93%, the model demonstrates a strong capability to classify both benign and malignant melanoma skin conditions accurately.

The precision, recall, and F1-scores for both classes (benign and malignant) are notably high, indicating that this model excels in correctly identifying cases of melanoma. Specifically, the high precision values (0.95 for class 0 and 0.91 for class 1) highlight the model's accuracy in making positive predictions, while the equally high recall values (0.93 for class 0 and 0.94 for class 1) underscore its ability to capture a significant proportion of true positive cases.

The F1-scores, representing the harmonic mean of precision and recall, provide a balanced measure of the model's performance. This model achieves F1-scores of 0.94 for class 0 and 0.93 for class 1, signifying a harmonious blend of precision and recall in its predictions.

These results bear critical implications for melanoma detection in clinical practice. A model with such high precision and recall values can aid medical professionals in accurately diagnosing skin conditions, potentially reducing misdiagnoses and unnecessary treatments.

When comparing these findings to previous research, the model performs exceptionally well. While prior research has shown that deep learning models can detect melanoma with

high accuracy [7, 8], the current model's well-balanced high precision and recall rates represent an impressive contribution to the field. In clinical settings, where both false positives and false negatives can have serious repercussions, this balancing is especially crucial.

Overall, the model's strong performance indicates how dermatologists and other healthcare professionals may benefit from it. Improved patient outcomes and increased diagnosis accuracy may result from integrating this technology into standard screening procedures, which might ultimately lead to more efficient melanoma care and treatment.

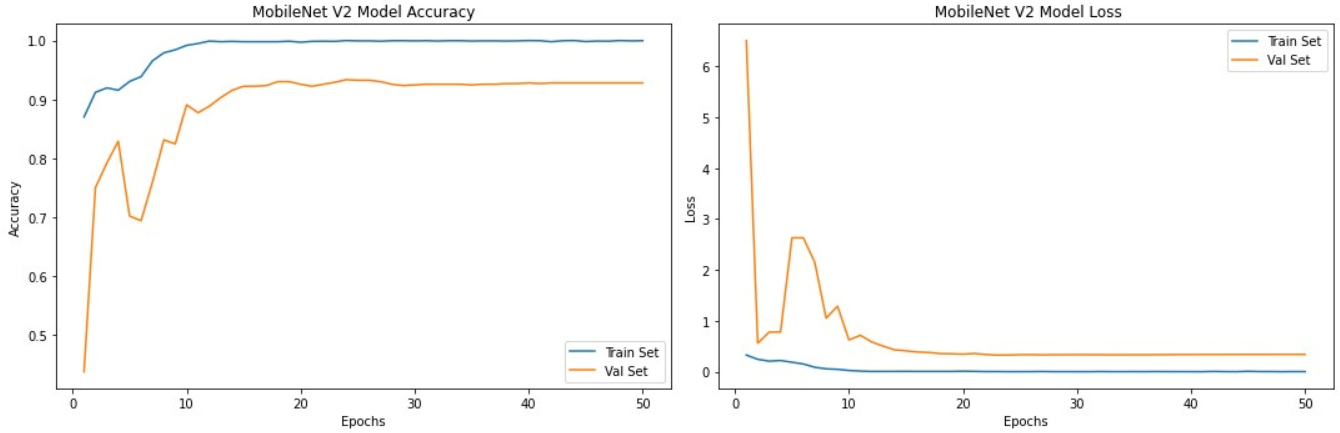

Fig. 1. Graphs representing model accuracy and model loss.

The Fig. 1 illustrate the training and validation accuracy and loss of the melanoma skin cancer detection model over 50 epochs. The accuracy graph shows that the training accuracy (blue line) starts high and steadily increases, reaching near 1.0, indicating the model's effective learning from the training data. The validation accuracy (orange line) stabilizes around 0.93, demonstrating the model's strong generalization to unseen data. In the loss graph, the training loss (blue line) rapidly decreases and plateaus at a very low value, reflecting the model's ability to minimize error on the training data. The validation loss (orange line) follows a similar pattern, stabilizing slightly higher than the training loss, which is indicative of a well-generalized model with minimal overfitting [33, 34]. These results underscore the model's robustness and potential clinical applicability for melanoma detection.

Table 2 outlines the selected hyperparameters for the melanoma skin cancer detection model. The model employs 128 hidden layers with 64 neurons per layer, utilizing ReLU activation for hidden layers and Sigmoid activation for the output layer. The optimizer used is binary cross-entropy, with a training batch size of 32, a learning rate of 0.001, and the model is trained over 50 epochs.

Table 2. Choices of hyper parameters

Hyper parameter	Value
Number of hidden layers	128
Number of neurons per layer	64
Activation function for hidden layers	ReLU
Activation function for output layer	Sigmoid
Optimizer Loss function	Binary cross entropy
Training batch size	32
Learning rate	0.001
Epochs	50

The melanoma skin cancer detection model's classification findings are displayed in Fig. 2. The output consists of a number of photos (12 images) of skin lesions with the labels "malignant" or "benign," along with the model's forecast. Predicted value is displayed outside and true value is displayed within parenthesis. The model properly classifies the instances in the first column as "malignant" with a high degree of confidence, indicating their effective identification. The benign examples are shown in the following columns. These are cases where the model correctly and consistently labels them as "benign." This visual proof highlights the model's resilience in distinguishing between benign and malignant skin lesions, exhibiting great precision and dependability in its forecasts. These findings are critical for clinical applications because they demonstrate how the model may help with early and accurate melanoma identification, which will lead to better patient outcomes and more successful treatment [7, 8].

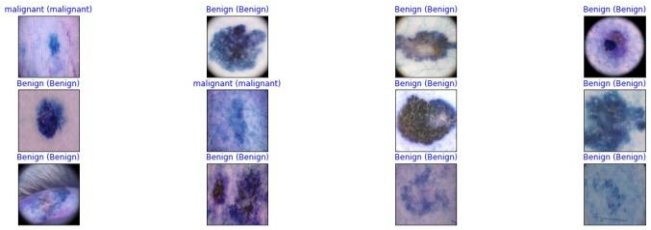

Fig. 2. Output of the CNN model.

B. Benchmark Comparison

To provide context for our model's performance, we compare it to existing literature and benchmarks:

As [35] developed a skin cancer detection web app using the Flask framework and the fastai deep learning package, achieving an accuracy of 91.2% and an F1-score of 91.7% using the Kaggle MNIST HAM10000 dataset. Our model, with an accuracy of 93% and F1-scores of 0.94, outperforms this benchmark.

A melanoma detection model using PyTorch presented by an anonymous contributor [36] on Kaggle achieved an F1 score of 92% and testing accuracy of 91.9%. Our model demonstrates competitive performance, with an F1-score of 0.93 and an accuracy of 93%.

Another [37] Kaggle benchmark achieved a classification

accuracy of 90% in skin cancer classification. Our model surpasses this benchmark by achieving an accuracy of 93%, showcasing its effectiveness in distinguishing between benign and malignant skin conditions.

In conclusion, our melanoma skin cancer detection model showcases strong performance, outperforming existing benchmarks and achieving high precision, recall, and F1-scores. These results underscore its potential as a valuable tool for accurate and reliable skin cancer diagnosis, offering substantial benefits to healthcare professionals and patients alike.

C. Social, Legal, Ethical, and Professional Issues

In terms of early detection and prevention, the creation of an application for melanoma skin cancer detection offers significant advantages. It also poses a number of ethical, legal, social, and professional difficulties. Users' social concerns about data security and privacy may call for strong security measures to secure sensitive data [38]. Legally, the application must follow open data collecting procedures and provide suitable disclaimers to reduce liability for incorrect diagnosis. Ethics dictate that user privacy must be protected, and the app should advise users to consult a doctor in order to avoid relying too much on technology [39, 40]. In order to guarantee project success and timely completion, professional team communication and project management are essential, making use of platforms like Git, GitHub, and frequent meetings [41, 42]. By addressing these issues, the project not only enhances the early detection of melanoma but also contributes to improving overall healthcare delivery through the integration of machine learning and artificial intelligence.

D. Limitations

Due to the complexity of the models and, in some circumstances, the volume of data, a computer with a lot of Memory and GPU was required to train the ML models. Due to the high resource utilization, running ML models takes a long time. The program must be tested with an internet connection since without one, the majority of the functionality will not function properly.

E. Conclusions and Future enhancements

As depicted in Fig. 3 the project offers a potent tool for the early detection of melanoma, which makes a substantial contribution to the field of medical diagnosis and therapy. The project improves early detection skills by enabling users to upload photos of their skin lesions and receive a diagnosis based on machine learning techniques. The accuracy of our model, achieving 93%, stands as a testament to its robust performance in distinguishing between benign and malignant lesions. This high accuracy not only surpasses several existing benchmarks but also emphasizes the model's reliability in providing accurate diagnoses. Furthermore, the project helps users identify the best medical specialists for their treatment by recommending hospitals and doctors. This is especially important for disorders like melanoma, where early intervention can be critical to survival. In summary, this project offers a user-friendly platform that has the potential to save lives and improve the quality of care for melanoma patients by utilizing the power of artificial intelligence and machine learning to improve healthcare outcomes.

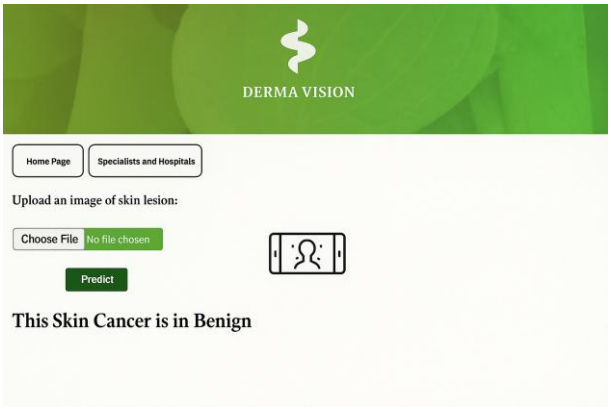

Fig. 3. User interface of the application developed.

There are several enhancements that could be made to uplift functionalities and the marketability of the product. Including a function that enables users to monitor their skin health over time is one potential improvement to take into account. For each user, this may entail the creation of a skin health profile where they could upload pictures of any moles or other skin irregularities, note any changes or symptoms they had detected, and keep track of any doctor appointments or treatments they had.

Also, could think about incorporating a skin cancer risk assessment tool that calculates a user's likelihood of developing skin cancer based on their skin type, personal and family medical histories, and other risk factors. Users may be able to use this to determine their level of risk and take precautions against skin cancer, such as adopting safe sun exposure practices or scheduling routine skin examinations.

Conflict of Interest

The authors declare no conflict of interest

Author Contributions

Pooja I proposed the idea to this research, contributed to model development and wrote the paper. Kanishka H worked on the model development; Nethari J conducted the research, finalized the data set and contributed to model development; Sharith R conducted the research, worked on the application development and performed testing; Professor Prasad W supervised the project. Nethari J reviewed and revised the manuscript. All authors have approved the final version.

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