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SKIN CANCER DETECTION USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT :

Deep learning, particularly Convolutional Neural Networks (CNNs), has become a crucial tool in medical image analysis, enabling more accurate and automated diagnostics. This study presents an advanced skin cancer detection system, focusing on Melanoma and Squamous Cell Carcinoma (SCC). By leveraging CNNs combined with DenseNet121 and ResNet50 for robust feature extraction and XGBoost for high-accuracy classification, the system is designed to improve early detection rates. Publicly available datasets, including the ISIC Archive and HAM10000, are employed for training and testing. Comprehensive preprocessing techniques, such as resizing, normalization, and data augmentation, are applied to enhance image quality and model robustness. DenseNet121 and ResNet50, known for their deep architectures and superior feature learning capabilities, extract critical patterns from the skin lesion images, while XGBoost performs precise classification. This approach not only improves accuracy but also offers a scalable and efficient solution for real-world clinical applications, aiming to significantly reduce mortality rates through early and precise detection of skin cancer.

Keywords: Skin Cancer, Melanoma, Squamous Cell Carcinoma (SCC), Image Processing, Convolutional Neural Networks (CNN), DenseNet121, ResNet50, XGBoost.

1. INTRODUCTION :

Deep learning, a subset of artificial intelligence, has revolutionized various fields, particularly medical image analysis. It enables systems to automatically learn complex patterns and make accurate predictions without extensive human intervention. Convolutional Neural Networks (CNNs), a key architecture in deep learning, are highly effective for image-related tasks due to their ability to extract spatial hierarchies and detailed features from images. CNNs have proven especially useful in medical diagnostics, where precise image interpretation is critical.
In this work, CNNs are applied to the challenging task of skin cancer detection, specifically targeting Melanoma and Squamous Cell Carcinoma (SCC). Traditional diagnostic methods, which rely heavily on manual inspection and basic image analysis, can be subjective and prone to errors. To address these challenges, we propose an advanced automated system that leverages CNNs to enhance the accuracy of skin cancer detection.

DenseNet121 and ResNet50, two state-of-the-art CNN architectures known for their deep feature extraction capabilities, are employed in this system. These networks capture intricate visual patterns from skin lesion images, patterns that may be missed through traditional analysis methods. Following feature extraction, the XGBoost classifier is applied, known for its efficiency and high accuracy, to classify the lesions into Melanoma and SCC.

To train and evaluate the model, publicly available datasets such as HAM10000 and the ISIC Archive are used, containing labelled images of various skin lesions. Pre-processing techniques including resizing, normalization, and augmentation are employed to ensure consistency and enhance the model's generalization. By combining CNNs for feature extraction and XGBoost for classification, this approach aims to provide a scalable, accurate, and reliable solution for early skin cancer detection, ultimately improving clinical outcomes by reducing diagnostic errors and enabling timely interventions.

2. LITERATURE REVIEW :

S.No	Title	Datasets Used	Model Used	Proposed System	Conclusion
1.	Skin Lesion Classification Using Hybrid Deep Neural Networks 2019 [1]	ISIC 2017	AlexNet, VGG16 and ResNet-18	Convolutional neural networks (CNNs) outperform classical methods in skin lesion classification. This work proposes an automated method using optimized deep features from AlexNet, VGG16, and ResNet-18.	This method achieves an 83.83% area under the ROC curve for melanoma classification and 97.55% for seborrheic keratosis classification.

				These features train support vector machine classifiers, whose outputs are then fused for final classification.	
2.	Skin cancer classification using Convolutional neural networks 2021 [2]	HAM10000 dataset.	Standard CNN	This paper explores using Convolutional Neural Networks (CNNs) to classify skin cancer from clinical images. The goals are to achieve over 80% accuracy, keep false negatives below 10%, and reach precision above 80%. The results show that our CNN model outperforms other methods.	Using the HAM10000 dataset, achieved over 80\% accuracy. Testing with augmented images yielded similar accuracy and precision. Results indicate that the Standard CNN method is highly effective for skin cancer diagnosis.
3.	Melanoma Detection Using Regular Convolutional Neural Networks 2017 [3]	ISBI 2016	LightNet	This paper uses Convolutional Neural Networks (CNNs) to classify melanoma images into benign and malignant. This automated approach assists dermatologists in early diagnosis. Our model, with a modest number of parameters and no prior image segmentation or cropping, was evaluated on the ISBI 2016 challenge dataset, achieving accuracy, sensitivity, and specificity comparable to state-of-the-art methods.	The modified LightNet architecture classifies melanoma images into benign and malignant without lesion segmentation or complex preprocessing. The results, obtained using the ISBI skin challenge dataset, are comparable to state-of-the-art methods while employing significantly fewer parameters.
4.	Skin Lesion Classification Using Hybrid Deep Neural Networks 2017 [4]	ISIC 2017	AlexNet, VGG16 and ResNet-18	Convolutional neural networks (CNNs) outperform classical methods in skin lesion classification. This work proposes an automated method using optimized deep features from AlexNet, VGG16, and ResNet-18. These features train support vector machine classifiers, whose outputs are then fused for final classification.	This method achieves an 83.83% area under the ROC curve for melanoma classification and 97.55% for seborrheic keratosis classification.
5.	Analyzing Skin Lesions in Dermoscopy Images Using Convolutional Neural Networks 2018 [5]	ISIC dataset.	CNN, Random Forest	The proposed system leverages deep convolutional neural networks for classification and incorporates hand-coded features like 166-D color histogram distribution, edge histogram, and Multiscale Color local binary patterns, analyzed by a random forest classifier.	By using convolutional neural networks on dermoscopic images, combined with hand-coded features analyzed by a random forest classifier, the method achieves 80.3% accuracy, 0.69 AUC, and 0.81 precision. For segmentation, a convolutional-deconvolutional model achieves a 73.5% Dice coefficient. This system aims to improve melanoma screening.

6.	The skin cancer classification using deep convolutional neural network 2018 [6]	Data set in this study was originated from related Internet sites.	ECOC-SVM in CNN- AlexNet Model	This paper develops a system for skin cancer using deep convolutional neural networks and ECOC SVM. We focus on classifying skin cancer with RGB images collected from the Internet. Features are extracted using a pre-trained AlexNet model, and ECOC SVM is used for classification.	Maximum values of the average accuracy, sensitivity, and specificity are 95.1 (squamous cell carcinoma), 98.9 (actinic keratosis), 94.17 (squamous cell carcinoma), respectively. Minimum values of the average in these measures are 91.8 (basal cell carcinoma), 96.9 (Squamous cell carcinoma), and 90.74 (melanoma), respectively.
7.	Classification Of Skin Lesions Using An Ensemble Of Deep Neural Networks 2018 [7]	ISBI 2017	AlexNet, VGGNet, GoogLeNet	This paper proposes a neural net architecture that aggregates robust convolutional neural networks (CNNs), achieving final classification based on the weighted output of AlexNet, VGGNet, and GoogLeNet. This framework allows all parameters and fusion weights to be optimized via backpropagation.	The proposed method efficiently organizes different CNNs into a single architecture, enhancing their cooperative performance. Tested on the ISBI 2017 challenge dataset, the ensemble method showed competitive results, outperforming individual CNNs. Future improvements could include adding more CNN members and addressing regularization issues to prevent overfitting. Increasing the training dataset size is also expected to enhance accuracy and reduce overfitting.
8.	Analyzing Skin Lesions in Dermoscopy Images Using Convolutional Neural Networks 2021 [8]	ISIC dataset	CNN, Random Forest	The proposed system leverages deep convolutional neural networks for classification and incorporates hand-coded features like 166-D color histogram distribution, edge histogram, and Multiscale Color local binary patterns, analyzed by a random forest classifier.	By using convolutional neural networks on dermoscopic images, combined with hand-coded features analyzed by a random forest classifier, the method achieves 80.3% accuracy, 0.69 AUC, and 0.81 precision. For segmentation, a convolutional-deconvolutional model achieves a 73.5% Dice coefficient. This system aims to improve melanoma screening.
9.	Smartphone-based Skin Cancer Detection using Image Processing and Convolutional Neural Network 2021 [9]	HAM10000 dataset	3 Layer CNN	In this study, the corroboration of image processing has been established with CNN in a smartphone-based skin cancer detection system to detect skin cancer from skin lesion images.	The proposed method has achieved 85% of accuracy with an F1-score of 86% on test data with Cohen's kappa coefficient of 0.70 and Matthews correlation coefficient of 0.71.

10.	Detection and Classification of Melanoma Skin Cancer Using Image Processing Technique 2023 [10]	ISIC dataset	CNN and SVM	Two methods are Proposed: using convolutional neural networks (CNNs) like AlexNet, LeNet, and VGG-16, and support vector machines (SVM) with an RBF kernel. The study also explores the relationship between model depth and performance with varying dataset sizes.	The CNN method, achieving accuracy of 94% with a loss of 17% when provided with identical data inputs. The SVM classifier achieved 86.6% accuracy.

3. ANALYSIS :

The studies demonstrate the effectiveness of hybrid deep neural networks for skin cancer classification. For instance, studies [1] and [4] highlight the successful integration of architectures like AlexNet, VGG16, and ResNet-18 with SVMs, achieving high accuracy, with AUC values reaching 97.55% for seborrheic keratosis and 83.83% for melanoma. Furthermore, studies [5] and [8] show that integrating CNNs with hand-coded features and random forests resulted in accuracies around 80.3% and an AUC of 0.69, emphasizing the value of combining different feature extraction techniques. An ensemble method combining networks like AlexNet, VGGNet, and GoogLeNet ([7]) has also demonstrated improved classification accuracy, showcasing the benefits of leveraging multiple CNN architectures. Additionally, the LightNet architecture ([3]) demonstrated competitive performance with fewer parameters, suggesting that specialized networks can be effective even with limited computational resources. Studies [6] indicate that combining CNN features with ECOC-SVM led to high accuracy for melanoma (94.17%) and squamous cell carcinoma (95.1%). Moreover, a smartphone-based detection system using a 3-layer CNN achieved 85% accuracy with an F1-score of 86%, highlighting the potential for lightweight architectures in real-world applications. These findings underscore the potential of hybrid approaches in enhancing skin cancer detection, paving the way for more accurate and accessible diagnostic tools.

In summary, the integration of DenseNet121 and ResNet50 for image feature extraction, combined with XGBoost for classification, has substantially enhanced skin cancer detection accuracy. This hybrid approach leverages the strengths of deep CNN architectures for feature extraction and the efficiency of XGBoost for classification. By utilizing these advanced methodologies, the model's predictive performance can be further refined. Employing additional techniques such as data augmentation and exploring hybrid ensemble methods will address existing challenges, improve classification precision, and provide deeper insights into skin cancer diagnosis. This approach aims to contribute to more effective and reliable screening strategies, ultimately advancing the field of skin cancer detection.

4. IMPLEMENTATION

The implementation of this system begins with gathering data from publicly available sources like the HAM10000 and ISIC Archive, which provide labeled images of skin lesions. Key preprocessing steps include resizing, normalization, and augmentation to ensure consistency and enhance model performance. Various algorithms, such as DenseNet121 and ResNet50 for feature extraction and XGBoost for classification, are implemented to improve detection accuracy. The flowchart below illustrates the step-by-step process of this implementation.

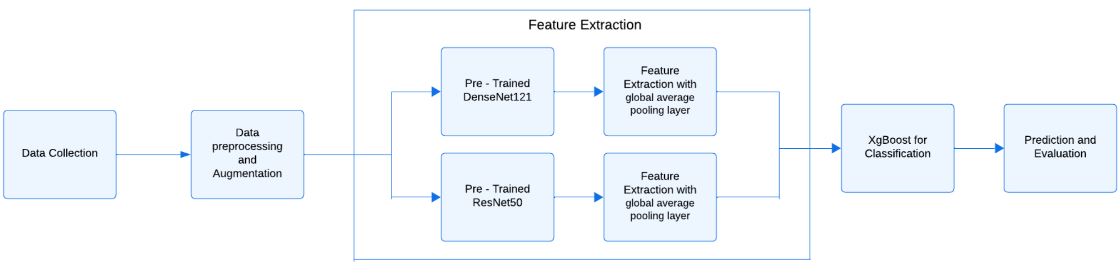

Fig. 1 Flowchart for Proposed Methodology

4.1 Data and Material

The primary dataset for this research is derived from the ISIC (International Skin Imaging Collaboration) dataset, sourced from Kaggle, which offers high-quality dermoscopic images specifically for detecting skin cancers, including Melanoma and Squamous Cell Carcinoma (SCC). To address the limited number of images in these categories, additional images were sourced from the HAM10000 dataset, also available on Kaggle, which is a comprehensive collection of skin lesion images. Merging both datasets significantly increases the sample size for Melanoma and SCC, resulting in a more balanced dataset for model training. This combined dataset enhances the model's ability to generalize, as it includes a variety of images representing different skin conditions, lighting scenarios, and lesion types, ultimately leading to more reliable and accurate classification outcomes.

To visually demonstrate the dataset utilized in this research, a selection of images from the merged dataset is presented below. These images include examples of Melanoma and SCC from both the ISIC and HAM10000 datasets. Their inclusion underscores the diversity and quality of the dataset, showcasing variations in lesion appearance, lighting conditions, and skin types that are vital for training a robust and generalizable model.

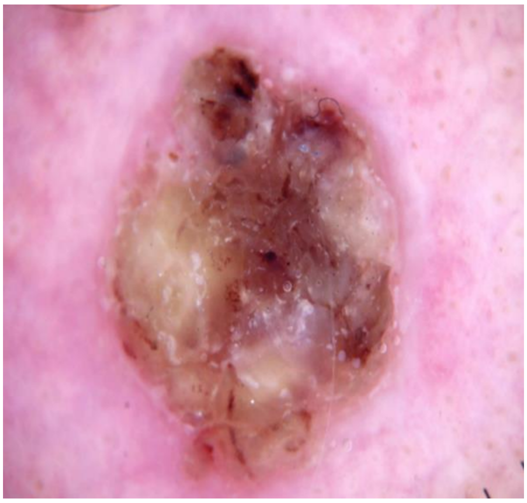

Fig. 2 Squamous Cell Carcinoma (SCC)

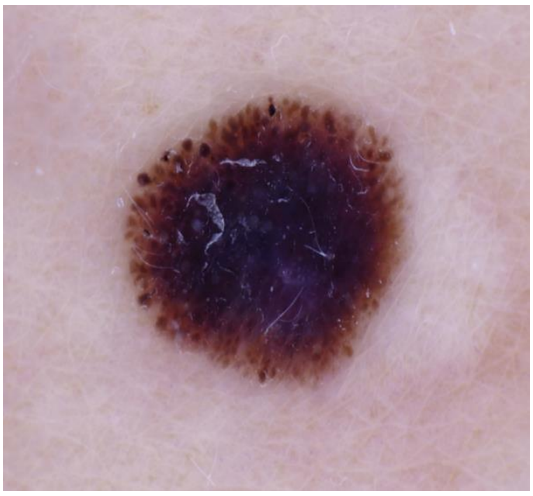

Fig. 3 Melanoma

4.2 Data Pre-processing

The preprocessing steps implemented in this research are meticulously designed to prepare the image data for effective feature extraction and classification. The process begins with rescaling, where pixel values are normalized to a range of [0, 1] by dividing by 255. This normalization is essential for enhancing the model training process, as it facilitates quicker and more effective convergence of the neural network.

Following normalization, all images are resized to a uniform dimension of 224x224 pixels. This resizing is critical to meet the input specifications of the DenseNet121 and ResNet50 models, which require images of this exact size. Maintaining consistent image dimensions ensures that these convolutional neural networks can accurately process the data and extract meaningful features.

Although the code does not explicitly incorporate data augmentation techniques, such as rotations, flips, or zooms, the fundamental preprocessing steps of rescaling and resizing provide a solid foundation for robust model training and evaluation. By normalizing pixel values and standardizing image sizes, the preprocessing effectively prepares the dataset for efficient feature extraction and accurate classification, thereby enhancing the overall performance and reliability of the skin cancer detection system.

4.3 Exploring Different Modeling Techniques

In this research, three different algorithms were implemented to classify skin lesions into Melanoma and Squamous Cell Carcinoma (SCC), utilizing deep learning techniques combined with powerful machine learning classifiers for enhanced accuracy. The first model, EfficientNetB0, is optimized for efficient scaling, balancing accuracy with computational resources, making it particularly effective for image classification tasks. The second approach employs DenseNet121 for feature extraction alongside LightGBM, a high-performance gradient boosting algorithm known for its speed and efficiency with large datasets. Lastly, the combination of DenseNet121 and ResNet50 for feature extraction, followed by XGBoost for classification, leverages the strengths of both deep learning architectures and robust machine learning methods to achieve superior classification performance.

4.3.1 Accuracy Calculation

Accuracy is a crucial metric for evaluating the performance of classification models, indicating the proportion of correct predictions made by the model relative to the total number of predictions. It serves as a fundamental measure of a model's effectiveness in distinguishing between different skin lesion types.

For manual accuracy calculation, the formula used is:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} * 100 \quad (1)$$

4.3.2 EfficientNetB0 Model

In this research, the initial model employed for skin cancer detection was EfficientNetB0, which is known for its optimized architecture that balances accuracy and computational efficiency. As a standalone model, it aimed to leverage deep learning capabilities for classifying skin lesions. However, the results indicated that EfficientNetB0 yielded relatively lower accuracy than anticipated. This outcome highlighted the limitations of using a single model for such a complex classification task, prompting the exploration of more advanced methodologies to enhance performance.

4.3.3 Hybrid Model: DenseNet121 + LightGBM

To address the shortcomings observed with the EfficientNetB0 model, a hybrid approach was developed, integrating DenseNet121 for feature extraction with the LightGBM algorithm for classification. DenseNet121's architecture effectively captures intricate features from skin lesion images, while LightGBM is known for its efficiency in handling large datasets and delivering quick predictions. The combination of these two advanced techniques led to improved accuracy compared to the initial single-model approach, demonstrating the advantages of merging deep learning with powerful machine learning algorithms. However, despite these enhancements in accuracy on training and test datasets, the model faced challenges when predicting on a separate set of unseen images.

Challenges in Predicting Unseen Data

The DenseNet121 + LightGBM hybrid model was subsequently tested on external images to evaluate its generalization capability. Unfortunately, this model experienced a notable decrease in prediction accuracy when applied to the unseen data. It particularly struggled with accurately classifying skin cancer types such as Melanoma and Squamous Cell Carcinoma (SCC). Even after multiple attempts at predicting the outcomes for both classes, the results consistently indicated lower accuracy levels. This issue underscored the need for further refinement in the model to improve its robustness in real-world applications where unseen data is prevalent.

4.3.4 Alternative Hybrid Model: DenseNet121 + ResNet50 + XGBoost

In response to the classification challenges encountered, the research explored an alternative hybrid model that combined DenseNet121 and ResNet50 for feature extraction, followed by the XGBoost algorithm for classification. This approach aimed to leverage the strengths of both deep learning architectures to enhance feature representation. Although this alternative hybrid model achieved slightly lower overall accuracy on the original dataset compared to the DenseNet121 + LightGBM model, it demonstrated significantly improved performance when predicting on external images. This enhancement in accurately distinguishing between skin cancer types, particularly Melanoma and SCC, emphasized the importance of employing multiple models for feature extraction, ultimately contributing to the development of more robust classification systems.

4.3.5 Model Comparison

The performance of the implemented models was rigorously evaluated using a standardized testing set, consisting of 16 images from each class, Melanoma and Squamous Cell Carcinoma. The results revealed notable differences in classification accuracy among the three approaches. EfficientNetB0 achieved an accuracy of **77.5%**, reflecting its potential but indicating limitations in tackling the complexities of skin cancer classification. On the other hand, the hybrid model of DenseNet121 + LightGBM demonstrated impressive accuracy at **91.58%**, showcasing its ability to capture intricate patterns in skin lesions effectively.

However, despite its high accuracy on the training dataset, the DenseNet121 + LightGBM model faced significant challenges when predicting on unseen data. This discrepancy highlighted its inability to generalize well, particularly with skin cancer types, which is a critical requirement for practical clinical applications. As a result, the focus shifted to the alternative hybrid model combining DenseNet121 and ResNet50 for feature extraction, followed by XGBoost for classification. This model achieved an accuracy of **87.50%**, striking a balance between performance and generalization capability. The XGBoost classifier effectively leveraged the features extracted from both deep learning architectures, leading to improved robustness in distinguishing between Melanoma and SCC, even in unseen data scenarios. To visually communicate these findings, a bar graph was created, illustrating the accuracy of each model, further emphasizing the strengths of the DenseNet121 + ResNet50 + XGBoost approach in delivering reliable and consistent classification results for skin cancer detection.

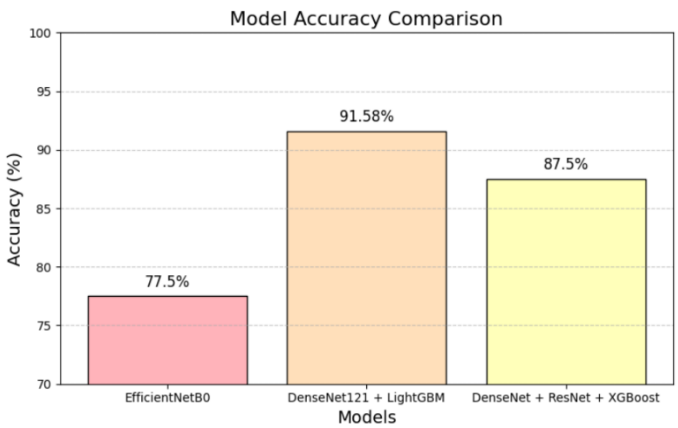

Fig.4 Comparison of Models

4.3.6 Model Performance Evaluation on Unseen Data

In this section, the focus shifts to the evaluation of model performance on unseen data, specifically analyzing the effectiveness of the DenseNet121 + LightGBM and DenseNet121 + ResNet50 + XGBoost models. While the DenseNet121 + LightGBM model demonstrated satisfactory accuracy on the training dataset, it struggled to maintain that performance when applied to unseen data. To address this limitation, the DenseNet121 + ResNet50 + XGBoost combination was chosen for further evaluation. Both models were tested using unseen images sourced from the HAM10000 dataset, enabling a comparative analysis of their accuracies in predicting skin lesions. This assessment aims to highlight the model's robustness and reliability in real-world scenarios, providing insights into their effectiveness for skin cancer detection.

Work 1: Initial Predictions

In the initial round of predictions, the performance of the two models was assessed using the HAM10000 dataset, where 150 images from each class (Melanoma and Squamous Cell Carcinoma) were utilized for testing. The DenseNet121 + ResNet50 + XGBoost model exhibited a prediction accuracy of **87.67%**, demonstrating its effectiveness in capturing the nuances of skin lesions. In contrast, the DenseNet121 + LightGBM model showed a lower accuracy of **70.45%**, indicating its challenges in generalizing to unseen images. These results underscore the importance of model selection in achieving reliable predictions for skin cancer classification.

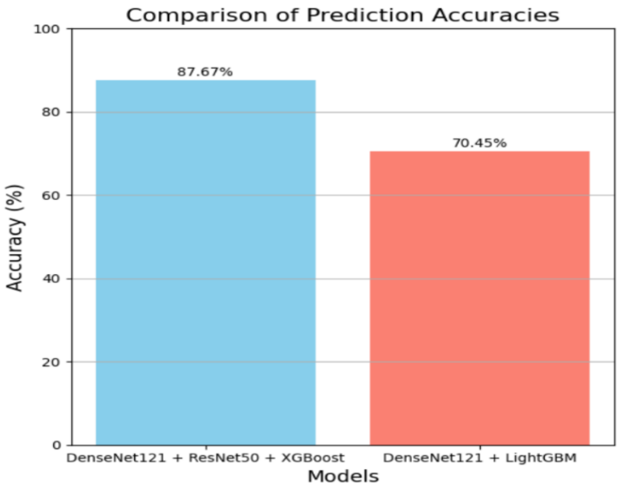

Fig. 5 Comparison of Prediction Accuracies 1

Work 2: Subsequent Predictions

In a follow-up round of predictions with the same setup, the models were tested again with the remaining images taken for training. The DenseNet121 + ResNet50 + XGBoost model further improved its performance, achieving an accuracy of **90.33%**, reflecting its robustness and ability to adapt to different data scenarios. Conversely, the DenseNet121 + LightGBM model showed a slight improvement in its accuracy, reaching **72.46%**. This consistent pattern of results highlights the superior predictive capabilities of the DenseNet121 + ResNet50 + XGBoost combination over the DenseNet121 + LightGBM model, reinforcing the selection of the former for effective skin cancer detection. The accuracy comparisons for both prediction rounds are illustrated in the graphs provided below, offering a clearer understanding of each model's performance.

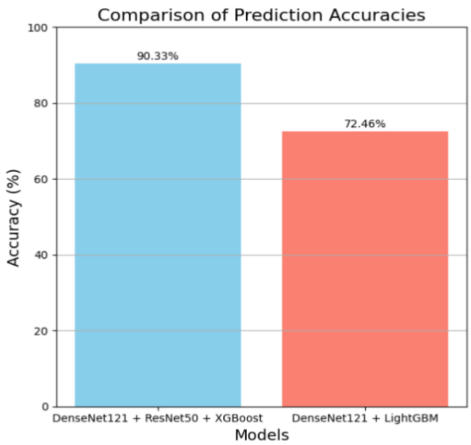

Fig. 6 Comparison of Prediction Accuracies 2

4.4 User-Friendly Interface for Skin Cancer Detection

Gradio is a powerful open-source library that enables the rapid creation of user-friendly interfaces for machine learning models. With its simple integration, Gradio allows developers to showcase their models interactively, making it easier for users to engage with the technology. In this research project, a Gradio-based user interface has been developed to facilitate the detection of skin cancer.

The UI allows users to upload images of skin lesions directly, after which the system processes the image and provides a classification result indicating whether the lesion is Melanoma or Squamous Cell Carcinoma (SCC). This intuitive design ensures accessibility for both healthcare professionals and patients, enabling quick and reliable assessments of skin conditions. By leveraging advanced machine learning algorithms behind the scenes, the interface delivers real-time predictions, empowering users with vital information for early intervention and treatment options. This user-friendly tool not only enhances the practical applications of the research but also demonstrates the potential for deploying AI solutions in clinical settings.

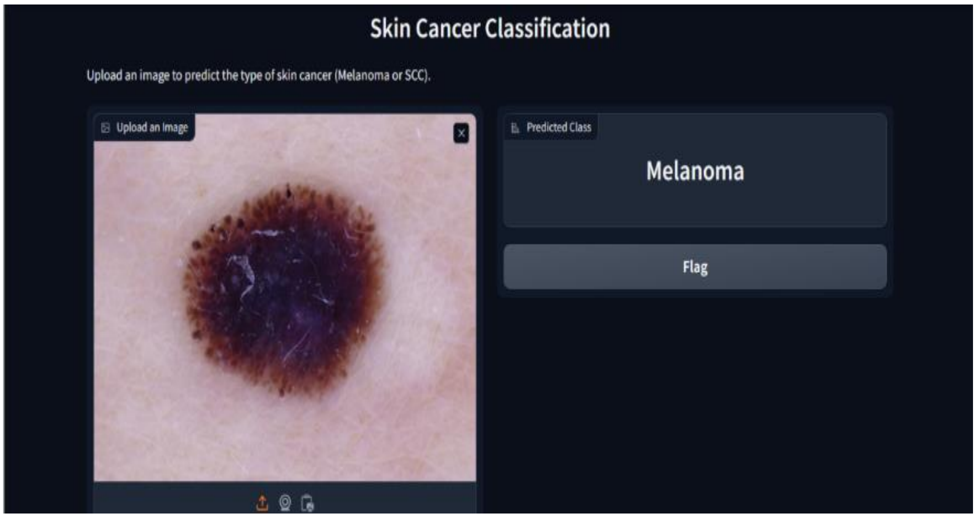

Fig. 7 User Interface for Classifying skin cancer types

INTERPRETATION AND CONCLUSION

5.1 INTERPRETATION

This research provides valuable insights into the performance of various models for skin cancer classification. Initially, EfficientNetB0 was utilized as a baseline model, achieving an accuracy of 77.50%. Although this outcome indicated moderate success, it underscored the necessity for further optimization to attain more dependable classification results.

To improve performance, a hybrid model was developed that combined DenseNet121 for feature extraction with LightGBM for classification, resulting in an accuracy of 91.58%. This combination showcased the benefits of merging deep learning models for feature extraction with advanced machine learning algorithms. However, when applied to images outside the training dataset, the DenseNet121 + LightGBM model attained only 70.45% accuracy on the first prediction, misclassifying several cases, especially when distinguishing between Melanoma and SCC. This highlighted the model's struggle with generalization to unseen data.

In addressing these limitations, an alternative hybrid model was investigated, incorporating DenseNet121 and ResNet50 for feature extraction followed by XGBoost for classification. While this model achieved an accuracy of 87.50% on the original dataset, it demonstrated enhanced performance on external images, with accuracies of 87.67% and 90.33% for the first and second predictions, respectively. Despite its slightly lower accuracy on the original dataset compared to the DenseNet121 + LightGBM model, the DenseNet121 + ResNet50 + XGBoost approach exhibited superior generalization, accurately classifying images from diverse sources and surpassing the previous model in practical prediction scenarios.

These findings emphasize the importance of evaluating models not only on their accuracy within the training dataset but also on their ability to generalize to new data. In this context, the DenseNet121 + ResNet50 + XGBoost hybrid model demonstrated greater reliability in predictions, making it a preferable choice for skin cancer detection tasks that require robust classification across varied datasets.

5.2 CONCLUSION

The hybrid model that integrates DenseNet121 and ResNet50 for feature extraction, along with XGBoost for classification, presents a more effective strategy for skin cancer detection. This model achieved an accuracy of 87.50%, slightly lower than the 91.58% accuracy obtained with DenseNet121 combined with LightGBM. However, the combination of DenseNet121 and ResNet50 facilitates a comprehensive extraction of detailed and robust features from dermoscopic images, effectively leveraging their strengths in capturing intricate patterns.

XGBoost enhances classification precision by adeptly utilizing these extracted features, demonstrating that the integration of multiple models for both feature extraction and classification significantly improves the ability to accurately distinguish between complex skin cancer types, such as Melanoma and SCC. These findings indicate that while single models may deliver higher overall accuracy, they often fall short in achieving precise classification. This research highlights the advantages of employing a hybrid model strategy, emphasizing that a combination of deep learning architectures and advanced classifiers yields a more reliable and nuanced approach to skin cancer detection.

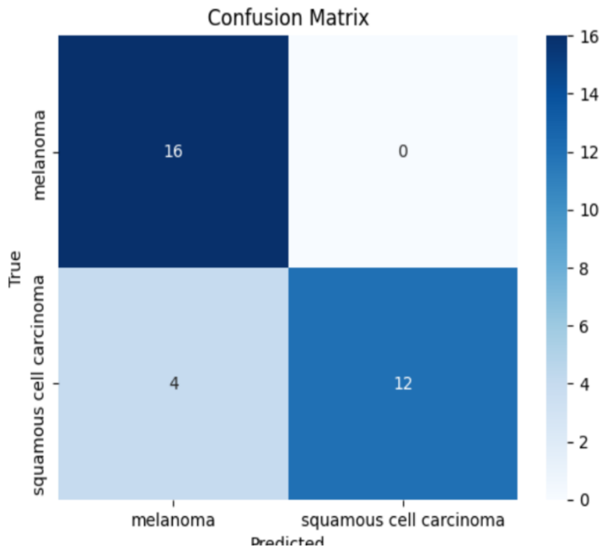

Fig. 8 Confusion Matrix

FUTURE WORK :

In future work, the classification system will be expanded to encompass a broader range of skin cancer types beyond Melanoma, Squamous Cell Carcinoma (SCC), and Basal Cell Carcinoma (BCC). This expansion will incorporate additional skin conditions, such as Dermatofibroma and Benign Keratosis-like Lesions (BKL), thereby enhancing the diversity of the dataset. Advanced deep learning architectures will be employed to achieve more accurate multi-class classification, with a focus on improving data augmentation techniques. Optimizing classification algorithms and utilizing cross-validation methods will be essential to ensure robust performance across all skin cancer types. Furthermore, the development of real-time classification systems will be prioritized, along with evaluations of their clinical usability to better support healthcare professionals in diagnosing various skin cancers.

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