Automating Melanoma Detection for Early Diagnosis using Conventional Machine Learning and Deep Learning Techniques

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ABSTRACT
Melanoma poses a significant global health threat, where early and accurate detection is crucial for improving patient survival rates. However, the visual diagnosis of skin lesions is often subjective and challenging due to the high similarity between benign moles and early-stage melanoma. This paper addresses this challenge by developing and evaluating a robust automated system for distinguishing between benign moles and melanoma using machine learning and deep learning techniques. A key aspect of the methodology was a hybrid feature engineering approach, combining clinically inspired ABCDE rule metrics with textural features from Local Binary Patterns (LBP) and color statistics. Several classification models were systematically evaluated, including traditional machine learning algorithms (Support Vector Machine, K-Nearest Neighbors, and Random Forest) and deep learning architectures (MobileNetV2 and AlexNet) on the Melanoma Skin Cancer Dataset. The experimental results demonstrated the superiority of the proposed AlexNet model over all other models tested, which achieved an outstanding classification accuracy of 95.2% and an Area Under the ROC Curve (AUC) of 0.99. Further, the contribution of this paper is extended to a practical application. The "Smart Skin Analyzer" desktop application and a "Melanoma Detector" Android application were developed to translate the research into a tangible tool, aiming to achieve the goal of raising awareness and facilitating early melanoma detection.

Keywords
Melanoma, Skin Caner, MobileNetV2, AlexNet, and ABCDE

1. INTRODUCTION
Melanoma stands as one of the most perilous and rapidly spreading forms of cancer globally [1]. This aggressive malignancy primarily originates from the abnormal proliferation of skin cells. While spontaneous development is common, several critical factors significantly elevate an individual's susceptibility, including a family history of melanoma, smoking, alcohol usage, excessive and unprotected exposure to ultraviolet radiation, and so on. Clinically, these skin lesions are broadly categorized as either benign or malignant. Moles [2] [3], a common manifestation on the skin, are typically benign growths, yet a subset can tragically transform into malignant tumors. Despite advancements in dermatology, radical clinical detection of melanoma remains notably challenging, often leading to diagnostic complexities due to its varied appearances and subtle early indicators. This inherent difficulty underscores the urgent need for more precise and objective diagnostic tools to improve early intervention and patient outcomes.

Over the past few decades, computer-aided diagnosis systems have diversified significantly. In order to detect cancer, traditional computer vision algorithms are mostly employed as classifiers to extract a wide number of features, such as shape, size, color, and texture. Artificial intelligence (AI) [4] is now capable of handling these issues. In order to identify cancer cells, the medical industry uses the most approved deep learning architectures, including recurrent neural networks (RNN), convolutional neural networks (CNN), and deep neural networks (DNN) [5]. Skin cancer can also be successfully classified using these models.

This work introduces a robust methodological framework for automated melanoma diagnosis, meticulously evaluating distinct approaches in parallel. The processed data is used to explore two primary diagnostic paradigms. The segmented images are fed into traditional machine learning classifiers such as SVM, KNN, and RF. In a parallel pathway, state-of-the-art deep learning architectures, including MobileNet and AlexNet, are directly employed as end-to-end classifiers, leveraging their inherent ability to learn intricate features from the processed images. The performance of all these independently developed models is then rigorously assessed. A significant contribution of this study lies in selecting the best-performing model as the foundation for developing a practical and accessible web-based system and a mobile application. This ultimately aims to provide a deployable solution for enhanced skin cancer detection, capitalizing on the most effective algorithmic approach identified.

The remaining sections of the paper are divided as follows: The second section focuses on studies related to melanoma and presents the most important problems and contributions of each study. This is followed by section 3 on the research methodology and its details. The most important results obtained, along with the necessary interpretations, are presented in the fourth section. Finally, the research conclusions and the most important recommendations are presented in Section 5.

2. LITERATURE REVIEW

Melanoma, a highly aggressive form of skin cancer, is characterized by the formation of malignant tumors on the skin. Dermatological photographs are instrumental in its detection. Leveraging high-performance imaging in conjunction with machine learning has proven highly effective in identifying skin cancer with remarkable efficiency [6].

Mohammad and Esraa [7] used 13 deep transfer learning models to facilitate the early and efficient identification of melanoma. While the system achieved accuracy for specific cancer types, the overall classification accuracy stood at 82.9%, a result attributed to factors such as dataset imbalance, limited image representation in certain categories, and the large number of classes. These factors likely contributed to the overall accuracy, suggesting areas for future improvement in dataset collection, balancing techniques, or more advanced model architectures designed to handle such complexities.

Another study by Ghadah [8] aimed to enhance precision in the diagnosis of skin cancer, particularly melanoma, from dermoscopic images using deep learning techniques and classifying skin lesions into seven distinct types. The core of the classification system utilizes a Convolutional Neural Network (CNN), specifically a modified version of ResNet-50. The paper explicitly mentions using an unequal sample of seven kinds of skin cancer from the HAM10000 dataset. This is a significant problem in medical image classification, where some lesion types are much rarer than others.

In the realm of dermatological diagnostics, a notable contribution by Walaa et al. [9] presents a deep learning-based approach for skin cancer detection using skin lesion images. This study leverages the power of convolutional neural networks (CNNs) to analyze visual characteristics within dermoscopic and clinical images, aiming to enhance the accuracy and efficiency of diagnosing various forms of skin cancer, including melanoma. The research, like many deep learning applications, inherently faces challenges related to the need for extensive, high-quality, and diverse annotated datasets to prevent bias and ensure robust generalization across varied patient populations and image acquisition conditions.

In the same context, Tembhurne et al.[10] present a novel proposal of merging machine learning and deep learning techniques to develop the skin cancer detection system. The deep learning model uses state-of-the-art neural networks to extract features directly from images, while the machine learning component processes features obtained through techniques like Contourlet Transform and Local Binary Pattern Histogram. Recognizing that meaningful feature extraction is crucial for any image classification problem, the designed model achieves a higher accuracy of 93% by effectively combining these manually engineered and automatically derived features. Despite the high accuracy, the remaining errors can be extremely critical in a cancer diagnosis context.

Nambisan et al. [11] developed a system fusing U-Net++ deep learning segmentation of irregular networks with classical hand-crafted features for melanoma diagnosis, using an annotated database. While achieving a recall and accuracy increase over deep learning-only models, key challenges include the reliance on limited manually annotated data, which impacts generalization. Moreover, features of the identified irregular networks were analyzed using the random forest classifier, linear SVM, RBF SVM, decision trees, and neural networks. Fusing these features with the deep learning results for a set of 1000 images of melanomas and benign lesions showed an improvement in the area under the curve for melanoma identification.

Another challenge of melanoma detection using the methodology of ensemble learning in the context of deep neural networks to improve predictive performance is presented by Mamun et al. [12]. Specifically, the authors focus on combining multiple pre-trained, state-of-the-art deep learning models (e.g., Inception, ResNet, VGG). The core methodology typically involves training these individual models on a common dataset, extracting their learned representations or predictions, and then fusing these outputs through various strategies such as weighted averaging, stacking, or majority voting to arrive at a final, more robust prediction. A key problem addressed by the research is the inherent limitations of single deep learning models, which, despite their power, can suffer from sensitivity to initial conditions, local optima, and less diverse feature learning.

A hybrid model amalgamating the strengths of two renowned convolutional neural networks (CNNs), VGG16 and ResNet50, presented by Ghosh et al. [13]. The research also highlighted the critical importance of comprehensive data preprocessing, detailing techniques like image resizing, color normalization, and segmentation to ensure the quality and dependability of the data used for training. Fundamentally, this study underscores the significant potential of artificial intelligence (AI) and deep learning (DL) in transforming skin cancer diagnostics, offering valuable perspectives on their wider applicability across various medical fields.

Ghosh et al. [14] develop a skin cancer detection system by extracting diverse image features using DCNN, Capsule Networks (Caps-Net), and Vision Transformer (ViT) frameworks. These extracted features then feed into an ensemble model comprising five machine learning algorithms: Random Forest, XGBoost, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression. This ensemble, which operates on a majority voting mechanism, significantly boosts overall performance. Notably, the resulting lightweight ensemble model achieves 91.6% accuracy on the melanoma skin cancer dataset.

Another interesting investigation by Nguyen et al. [15] delves into the application of machine learning techniques for enhancing skin cancer detection, particularly melanoma. The study rigorously evaluated various models, with CNNs consistently emerging as the most effective in distinguishing between malignant and benign lesions, achieving an accuracy score of 92.10%. While traditional machine learning algorithms such as RF and SVM also demonstrated strong performance, offering viable alternatives where model interpretability is paramount. The study acknowledges that despite CNNs presenting the most promising results, their successful integration into clinical practice necessitates overcoming challenges related to interpretability, dataset variability, and ensuring robust real-world generalization.

A comprehensive overview study of the state-of-the-art in applying AI to melanoma diagnostics was given by Hoda and Ali [16] Ahmed and Amina. their work included over than 30 studies published between 2016 and 2024 The methodology employed by the reviewed studies primarily revolves around deep learning architectures, particularly Convolutional Neural Networks (CNNs) such as DenseNet and other deep CNN variants, often leveraging large, publicly available dermoscopy image datasets like HAM10000 and ISIC for training and validation. Despite the promising advancements, the review highlights several recurrent problems in the field. These include challenges related to data diversity and accessibility. Computational resource requirements for training and deploying these sophisticated models also present a practical challenge.

To sum up, previous studies have demonstrated the transformative potential of deep learning, particularly CNNs and hybrid approaches, in improving the accuracy of melanoma detection. Notwithstanding the notable advancements, issues with dataset imbalance, restricted generalizability as a result of data diversity, and the requirement for interpretable models still exist. This emphasizes the ongoing need for sound approaches that strike a balance between clinical relevance, real-world applicability, and performance.

3. The Proposed Methodology

The detection of skin lesions (moles vs. melanoma) goes through various phases: image acquisition, preprocessing of data, feature extraction, and classification. Figure 4.1 illustrates the structure of the proposed system.

3.1 Image Acquisition

The Melanoma Skin Cancer Dataset [17] is a publicly available resource widely used in research involving skin cancer detection. Therefore, it was chosen in this paper to conduct experiments. The Benign lesion images consist of 600, and the Malignant lesion images consist of 600.

3.2 Preprocessing

In computer vision-based melanoma diagnosis systems, the image preprocessing step is essential since it aims to improve the quality of skin images before further analysis. Pre-processing essentially identifies the lesion in subsequent procedures by removing anything undesired except the lesion. Artifacts are low contrast, and hairs, veins, and other things are undesirable [18]. Several techniques were employed on the images in this research to further enhance performance in subsequent stages, which will be presented in the following sections.

3.2.1 Hair Removal

To remove hair, convert the color image to grayscale. Next, a morphological operation is applied with a large kernel (17x17) to highlight dark hair regions against the lighter skin. A binary threshold identifies these hair regions, creating a mask. Finally, the cv2.inpaint function is used to remove the identified hair by interpolating surrounding pixel values, effectively "filling in" the hair areas and producing a cleaner image. Figure 2 presents an image after removing hair.

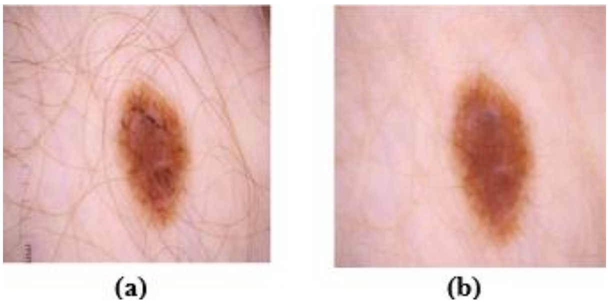

Fig 2: Removing hair process, a: original image b: image after removing hair.

3.2.2 Contrast Enhancement

Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to address uneven lighting and poor image contrast. CLAHE adaptively enhances local contrast by operating on small image tiles [19], thereby improving the visualization of subtle lesion structures like pigmentation networks and streaks without over-enhancing noise.

3.2.3 Denoising

To banish the distracting random noise that often sneaks in during image capture, we first unleash a Gaussian blur filter (specifically, cv2.GaussianBlur). With a delicate 3x3 kernel, this aims to perform a subtle smoothing operation designed to quiet the noise without sacrificing critical image features. After this precise noise reduction, every image undergoes a uniform transformation, meticulously resizing to 128x128 pixels using cv2.resize. Figure 3 illustrates the image after these operations.

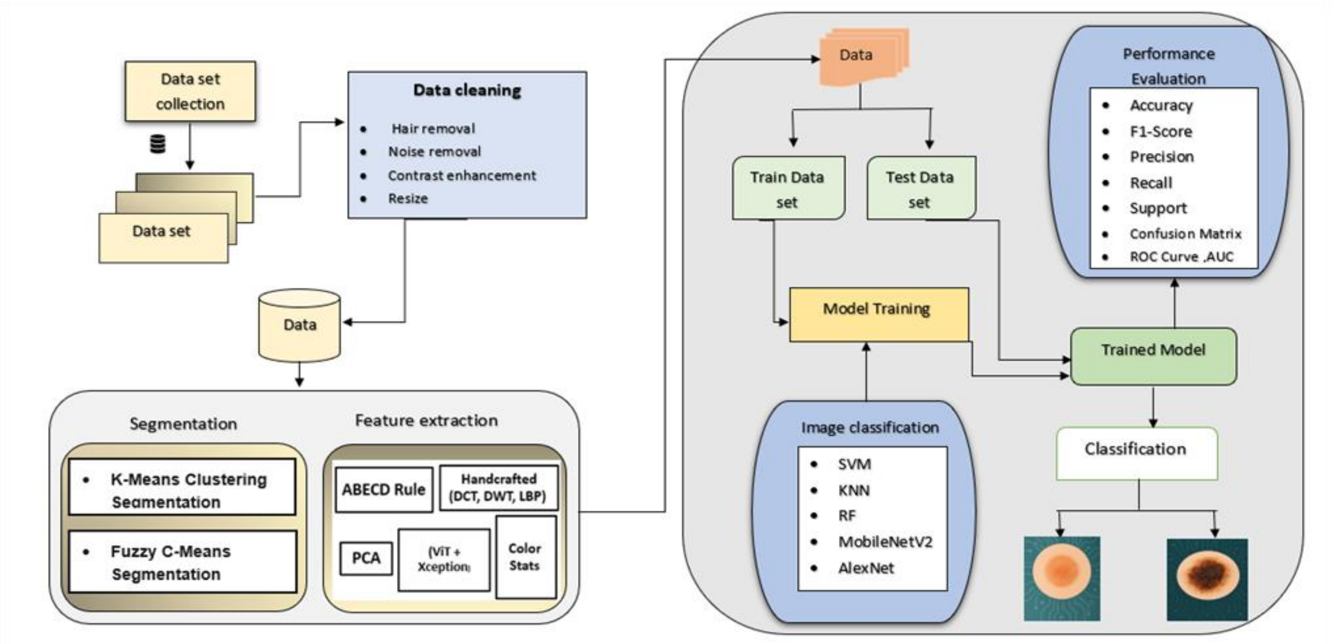

Fig 1: The framework of the proposed system

(a) (b)

Fig 3: Contrast Enhancement process, a: input image b: Enhanced image

3.2.4 Data Augmentation

To dramatically boost the diversity and size of our training data without hogging extra storage, Dynamic data augmentation was utilized [20]. This smart approach dynamically creates new, transformed versions of the original images as the model learns. The model sees a constantly fresh stream of variations, which greatly improves its ability to generalize to new, unseen images and slashes the risk of overfitting. The specific transformations used in this work include rotation, horizontal and vertical shifts, zooming, and horizontal flipping.

3.3 Image Segmentation

The image segmentation stage is performed to precisely delineate the region of interest (ROI) of the skin lesion from the surrounding healthy skin. The K-Means and Fuzzy C-Means methods have been utilized in this paper. The K-means clustering method provides unsupervised image segmentation. It groups pixels into (N) clusters (often 2 for foreground/background) by color proximity to centroids. The image is reshaped and clustered, and the resulting cluster labels form the segmentation mask. In the same context, K-Means, Fuzzy C-Means (FCM) methods allow pixels to belong to multiple clusters simultaneously with varying degrees of membership. Figure 4 illustrates the difference between the original image and the image following the segmentation process.

(a) (b)

Fig 4: The segmentation process, a: input image. b:segmented image

3.4 Feature Extraction

Once images are preprocessed and segmented, a rich collection of quantitative features is extracted to characterize the skin lesions by various algorithms. This involves the capture of traditional dermatological indicators, intricate textural patterns, and comprehensive color statistics. In this paper, the clinical ABCDE rule (Asymmetry, Border irregularity, Color variation, Diameter, and Circularity) [21] was translated into computational features to support melanoma detection. Specifically, asymmetry was calculated by mirroring the lesion, border irregularity was quantified using Canny edge detection, color variation was determined by pixel intensity standard deviation, diameter was derived from the largest contour's area, and circularity was computed using a shape regularity formula.

Also, Local Binary Patterns (LBP), color statistics, DCT, and DWT were chosen as effective techniques due to their strong ability to highlight subtle texture differences, which are critical for distinguishing malignant melanomas from benign nevi. To complement these, advanced deep learning approaches were also employed; features were extracted using pre-trained Vision Transformer (ViT) and Xception models, followed by Principal Component Analysis (PCA) for dimensionality reduction and optimal feature representation.

3.5 Classification Algorithms

Several classification models were systematically evaluated to distinguish between benign moles and melanoma. Both traditional machine learning algorithms and deep learning architectures were considered.

To distinguish between cancerous and non-cancerous skin lesions, both traditional and deep machine learning models were utilized in this study. For the traditional approaches, SVM, KNN, and RF were applied, with extracted features directly feeding into these classifiers. Additionally, deep learning models, specifically MobileNetV2 and AlexNet, were employed to leverage their advanced feature learning capabilities. The results of the proposed methods are tabulated in the next section.

4. DISCUSSIONS AND RESULTS

The skin cancer images have been collected from Kaggle [17]. To identify the most effective classification model, a variety of experiments were conducted. This approach began with establishing baselines using traditional machine learning algorithms, including SVM, KNN, and Random Forest. Then, MobileNetV2 and AlexNet have been applied as classifiers. This systematic approach allowed for a clear comparison of different classification paradigms. To provide a high-level overview of the final outcomes, Table 1 summarizes the performance metrics of all five models tested.

Table 1. Performance Metrics of Tested Models

Model	SVM	KNN	RF	Mobile NetV2	AlexNet
Input Image Size	96x96	96x96	256x256	256x256	128x128
Feature Extraction	ViT + Xception + PCA	ViT + Xception+ PCA	DCT, DWT, LBP	DCT, DWT, LBP and Rule ABCED	combined_features ABCED, LBP, Color Stats
Accuracy	0.91	0.71	0.86	0.92	0.95
Precision	0.91	0.80	0.86	0.92	0.96
Recall	0.91	0.71	0.84	0.92	0.95
F1-Score	0.91	0.69	0.85	0.91	0.95
AUC	0.97	0.84	0.94	0.97	0.99

From Table 1, it is noted that the AlexNet model achieved the highest scores across all key metrics. Before the chosen AlexNet model is thoroughly examined, the detailed results for each of the benchmark models will be illustrated in the ensuing sections.

In the initial experiment, the SVM model, leveraging feature vectors extracted using ViT and Xception architectures followed by PCA, served as an effective baseline, achieving a remarkable overall accuracy of 91% along with strong precision (0.91), recall (0.91), F1-score (0.91), and an AUC of 0.97. In contrast, the KNN method, utilizing the same feature extraction approach, yielded a lower accuracy of 71%, suggesting that its distance-based classification struggled with the complex feature space. The Random Forest (RF) classifier was then employed to assess the efficacy of ensemble learning with handcrafted features (DCT, DWT, LBP). This model achieved an improved overall accuracy of 86%, indicating the value of ensemble methods in capturing diverse patterns.

In the two most recent experiments, the deep machine learning techniques have been implemented. The MobileNetV2 model, employed through transfer learning and trained on handcrafted features combined with the computational ABCDE rule, achieved a high accuracy of 92%, surpassing all traditional machine learning methods. Finally, the AlexNet architecture, benefiting from a comprehensive set of combined features including ABCDE, LBP, and Color Statistics, demonstrated superior performance, yielding an impressive overall accuracy of 95.2% and an AUC of 0.99, confirming its exceptional capability in melanoma detection.

To validate the results of all experiments, various metrics were used in this paper to check the performance of the techniques used. Specifically, the confusion was used. All performance tests showed that the last experiment, in which a trained AlexNet model was used, was the best experiment. Figures 5, 6, 7, 8, and 9 illustrate the confusion matrix for these methodologies.

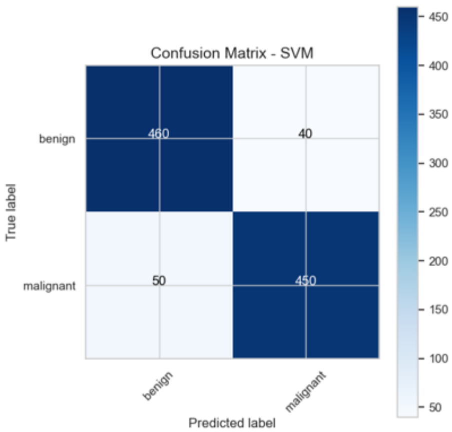

Fig 5: The confusion matrix of SVM

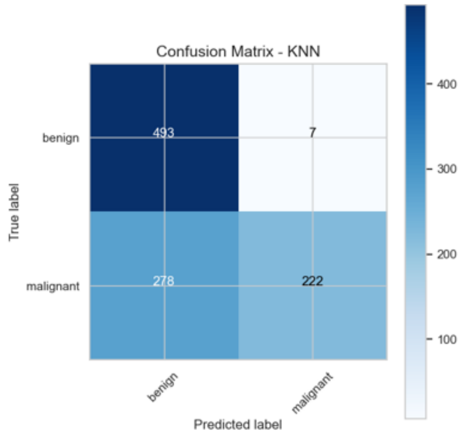

Fig 6: The confusion matrix of KNN

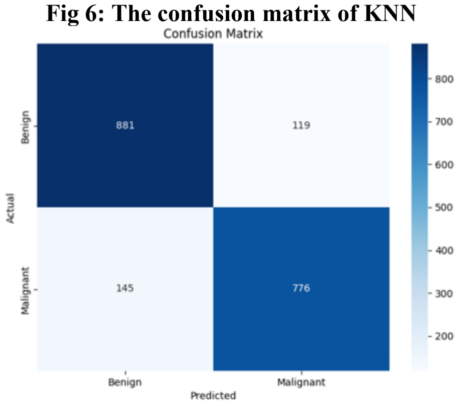

Fig 7: The confusion matrix of RF

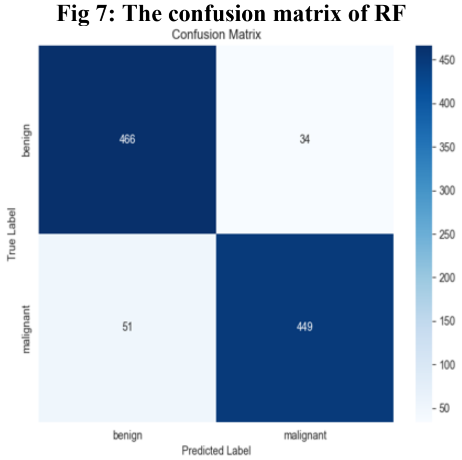

Fig 8: The confusion matrix of MobileNet

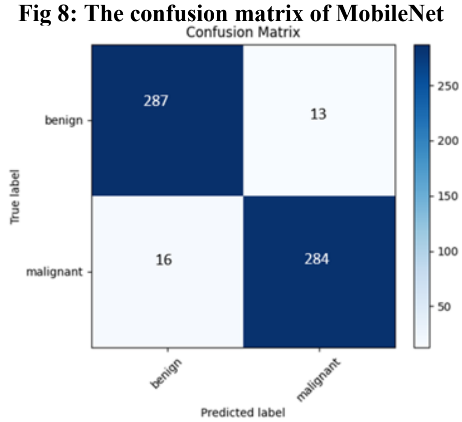

Fig 9: The confusion matrix of AlexNet

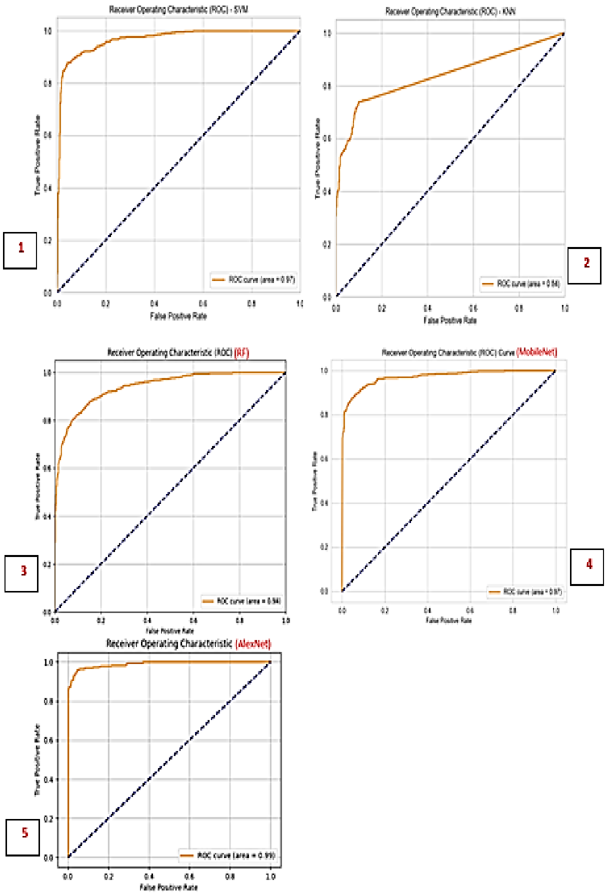

Fig 10: The ROC curve. 1:SVM 2:KNN 3: RF 4:MobileNet 5: AlexNet

Moreover, to assess and compare the accuracy of the algorithms, the ROC curve was plotted as shown in Figure 10. It is noted unequivocally that the AlexNet model exhibits the most robust performance, evidenced by its ROC curve demonstrating the highest Area Under the Curve (AUC) of 0.99. This exceptionally high AUC value signifies AlexNet's superior ability to effectively distinguish between melanoma and benign lesions across all possible classification thresholds, outperforming all other benchmark models. In comparison, while the SVM and MobileNetV2 models also showed strong discriminative capabilities with AUC values of 0.97 and 0.97, respectively, their curves lie slightly below that of AlexNet, indicating a marginally less optimal balance between sensitivity and specificity. The Random Forest model, with an AUC of 0.94, demonstrates a good performance, whereas the KNN model, having the lowest AUC of 0.84, suggests relatively weaker discriminative power compared to the other approaches.

4.1 Comparison with previous approaches

To contextualize the findings of the paper within the current research landscape, a comparative analysis was performed against the recent work by Güneş and Dönmez [22]. The work presents an ideal benchmark due to its contemporary nature and focus on the same classification problem. To facilitate a clear comparison, Table 5.2 summarizes the key methodological differences and performance outcomes between our model and the best-performing model reported by Güneş.

Table 2. The Performance Comparison Of The Proposed Approach With Previous Study

Feature / Metric	Güneş [53]	Our Proposed	Key Difference & Implication
Model Architecture	Custom CNN (4 Convolutional Layers)	AlexNet (Established Architecture)	Our model uses a deeper, more complex architecture known for robust feature extraction.
Feature Engineering	End-to-End Deep Feature Learning	Hybrid Approach ABCDE Clinical Rules, LBP Textural Features, Color Statistics	Our model is enriched with explicit, medically-relevant features, providing richer context than implicit learning alone.
Input Image Size	64x64 pixels	128x128 pixels	Higher resolution allows our model to capture more detailed features.
Accuracy	91.32%	95.2%	Our model achieves a 4% absolute improvement in accuracy, a substantial gain.
Sensitivity (Recall)	91.9%	95.0%	Our model is significantly more effective at identifying malignant cases.
F1-Score	92.0%	95.0%	The higher F1-score indicates a better balance and superior overall performance.
AUC	Not Reported	0.99	Our model demonstrates near-perfect class separability.

As shown in Table 2, the proposed system surpasses the benchmark across all reported metrics. The most significant factor contributing to this performance gap is our hybrid feature engineering methodology. While the benchmark study effectively showed that increasing CNN depth improves performance, it relied solely on the network's ability to learn features implicitly. In contrast, it explicitly injects high-level, domain-specific knowledge into the learning process. This fusion of handcrafted and deep-learned features provides the AlexNet architecture with a much richer and more discriminative input. Consequently, the 4% absolute improvement in accuracy and, more critically, the increase in sensitivity, underscore the value of our methodological choices.

The study's contribution extends beyond model development to practical application. A user-friendly prototype, the "Smart Skin Analyzer" desktop application, and a "Melanoma Detector" Android application were developed to translate the research into a tangible tool.

5. CONCLUSIONS

This paper embarked on a critical mission to engineer an advanced, automated system for melanoma detection using dermoscopic images. Leveraging a meticulously preprocessed, balanced dataset of 6,000 images, various machine learning and deep learning paradigms have been rigorously benchmarked. The comprehensive experimental analysis of this proposed model demonstrated the superiority of the proposed AlexNet model, which achieved an exceptional 95.2% overall accuracy and a remarkable Area Under the ROC Curve (AUC) of 0.99.

Furthermore, the evolution of this prototype into a comprehensive, multi-platform ecosystem featuring the "Melanoma Detector" Android mobile application and a supporting web platform represents a monumental stride towards democratizing early melanoma screening. By meticulously integrating the optimized AlexNet model and the full preprocessing pipeline directly onto mobile devices via Flutter and opencv_dart

While acknowledging limitations such as reliance on a single public dataset, this work lays a robust foundation for future endeavors. Subsequent efforts will focus on enhancing model robustness in real-world conditions, boosting interpretability with LIME and SHAP, ensuring scalable and secure integration into healthcare systems, and rigorously pursuing prospective clinical trials and regulatory approvals.

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