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ARTICLE

Enhanced SVM-Based Model for Skin Cancer Detection Using Dermoscopic Images

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Abstract

Introduction: Skin cancer is still a pervasive worldwide health concern, amid its increasing cases which continues to pose a burden on global health challenge. Melanoma, a very ferocious type of skin cancer, requires timely detection owing to its tendency to spread quickly throughout the body. Timely diagnosis markedly increases survival outcomes, but maintaining reliability in clinical evaluation remains an intractable problem despite advances in AI. Dermoscopy, a widely used non-invasive imaging technique, strengthens the visualization of deeper skin layers and significantly aids in recognizing abnormal lesions. However, interpreting these images is not straightforward, it requires years of expertise. Recent breakthroughs in artificial intelligence (AI) have created valuable prospects to improve skin cancer detection. While deep learning (DL) and machine learning (ML) models have each exhibited effectiveness in analyzing dermoscopic images, individually, these methods are limited by challenges. By blending the advantages of different algorithms, hybrid AI models have emerged as a powerful solution, which boost feature extraction, accuracy, and reliability in ways single models often cannot. By integrating synergies, such models support dermatologists with faster, more consistent diagnostic outputs, allowing skin cancers such as melanoma to be recognized sooner and treated more effectively.

Aim: In this work, we propose a SVM-based diagnostic approach that aims to improve the classification accuracy of lesions.

Method: A total of 5,000 dermoscopic images depicting nine different skin lesion types were utilized. For preprocessing, images were standardized using lesion segmentation, color normalization, resizing, and augmentation. EfficientNet-B7 (pre-trained on ImageNet) served as a feature extractor.

Results: The SVM-Based model approach demonstrated strong performance, achieving an accuracy of 88.00% and an AUC-ROC of 88.63%. Primarily, the model managed to deliver an outstanding malignant sensitivity of 99.00%. This means that the system detects almost every true case of cancer.

Conclusion: This research progressive advancement in the area of malignant metrics compared to the previous hybrid model (F1-score 93.00% and 91.00%), which further confirms its reliability and trust. This is achieved by combining the powerful representation features of EfficientNet-B7 with SVM classification, the model focused on detecting most malignancies and obtained low false negatives.

Keywords: EfficientNet-B7, Support Vector Machine, Skin Lesion Classification, Dermoscopic Images, Image Classification.

1.0 Introduction

Skin cancer remains an ongoing global public and health issue, notably due to its increase in incidence and associated fatalities due to late diagnoses. Global reports and data indicate that there are several million-skin cancer new cases each year, with tens of thousands of deaths due to melanoma. This underscores the growing demands for new and better approaches to enable timely and accurate detection of the disease (Rotemberg *et al.,* 2021; WHO and ILO, 2024). Conventional diagnostic methods are frequently time-consuming and open to interpretation, relying heavily on dermatologists' expertise, underscoring the need for faster, objective tools. Progress in medical imaging has enhanced automated detection of skin cancer Esteva *et al.* (*2*017).

Extensive analysis by Naqvi *et al.* (2023) demonstrated that deep learning algorithms, particularly convolutional neural networks (CNNs), outperform traditional ML methods in dermoscopic image classification. Their findings highlight the prospect of these AI systems to improve early detection and ease diagnostic workload in dermatology clinics.

The foundational work of Esteva *et al.* (2017) showed that deep CNNs can match expert dermatologists in classifying skin lesions, using tens of thousands of clinical images. More recent evaluations with standardized datasets, such as the ISIC archives, highlight the value of large, well-annotated dermoscopic collections for algorithm development (Tan and Le, 2019).

EfficientNet B7 performs well in transfer learning for high-resolution image tasks (Tan and Le, 2021). Research on human-computer collaboration further suggests that AI support can improve clinical diagnostic accuracy, demonstrating benefits beyond what a standalone algorithm alone can achieve (Tschandl *et al.,* 2020).

Support Vector Machines (SVMs) serve a very useful purpose in medical imaging. They are reliable in high-dimensional feature spaces and are easy to understand when features are well-defined. Existing works shows that using combined CNN feature extraction and SVM classification increases sensitivity in binary screening. This is particularly true when working with the deficient or imbalanced datasets (Behara *et al.,* 2024; Doğan and Özdemir, 2024)

A study by Shams *et al.* (2025) is the one that compared EfficientNet B0 with ResNet50 and MobileNet for multi-class skin disease classification. EfficientNet B0, with 99% accuracy and fewer parameters, is the best of the three models. This goes to show that EfficientNet models are best suited for medical imaging, especially in settings with limited resources. However, research on medical imaging is shifting more towards other aspects like fairness, interpretability, and clinical accuracy.

Daneshjou *et al., (*2021) showed that the EfficientNet model perform best on lighter skin tones, underscoring the urgent demand for inclusive collections and meaningful bias reduction (Alzakari *et al.*, 2024) proposed LesionNet, which joins SIFT and other handcrafted descriptors with CNNs for the classification of multi-class skin cancer. They showed that deep learning and traditional features could coexist. However, the lack of studies using EfficientNet or SVMs hinders strong conclusions on those. Choi *et al.*, (2024) developed an ensemble that joined the clinical ABCD rule with EfficientNetB0 and GradCAM visualization, achieving strong accuracy while improving interpretability for clinicians, though at the cost of higher computational complexity. Kanchana *et al.,* (2024) used all EfficientNet variants (B0–B7) for transfer-learning in skin cancer detection. It was reported that B7 offered the most effective trade-off between accuracy and efficiency, making it suitable for detailed lesion analysis, although challenges remained with rare malignant classes and limited diversity in patient populations.

Manole *et al., (*2024) appliedEfficientNetB3 based on the strengths of computational and time efficiency. The moderate performance of the resource-efficient model demonstrated its applicability to low resource healthcare settings. However, the study did not identify the applicability of traditional classifiers such as SVM in increasing the model sensitivity towards infrequently occurring lesion types.

Toprak and Aruk, (2024) developed an imbalanced and sensitive melanoma detection model focusing on enhancing malignant sensitivity through loss reweighting and improving recall. Although other studies developed imbalanced and sensitive melanoma detection, theirs was the first to focus on loss reweighting. However, the study was limited to older frameworks of convolutional neural networks (CNN) and did not benchmark the model performance of EfficientNet. Keerthana *et al., (*2023) described the hybrid model of CNN and SVM, as SVM is known to improve the accuracy of deep learning (DL) based classifiers in small imbalanced datasets. This is an illustration of the combined deep and classical learning approached. However, hybrid EfficientNet and SVM models remain unexplored. Venugopal *et al., (*2023) used a large, consolidated dataset which improved the classification model performance using a modified EfficientNet. The performance of the model was better than other conventional CNN and demonstrated the importance of scaling and fine-tuning

towards improving the model performance. The study, however, is limited to the end-to-end framework ignoring the incorporation of hybrid or posthoc classifiers to improve the robustness of the model (Nawaz *et al*., 2025).

Ghosh *et al*., (2024) recently proposed a hybrid model combining VGG16 and ResNet50 for dermoscopic skin cancer classification, achieving 98.8% accuracy. Despite strong results, the approach remained computationally demanding and struggled with fine-grained features, class imbalance, and overfitting. Building on these findings, this paper introduces a new hybrid model that integrates EfficientNet-B7 with an RBF-kernel SVM to improve accuracy and efficiency. It aims to address key screening challenges and enhance the reliable detection of malignant cases.

2.0 Experimental Set and Methodology

This research utilized a two-stage approach with specific aim to classify skin lesions into two categories, benign or malignant. The framework was set up to address an urgent need in the clinical setting for very accurate and timely diagnoses. The system uses EfficientNet-B7 for CNN dermoscopic images deep feature extraction and SVM for classification into the final classes.

This system architecture was designed for skin lesion analysis to obtain optimal accuracy and diagnostic confidence since EfficientNet-B7 is the leading feature extractor and SVMs have proven reliable in classification.

2.1 Dataset and preprocessing

The images used in this study are derived from the ISIC 2020 repository (Rotemberg *et al.,* 2021). The full repository had 33,126 dermoscopic images containing nine different skin types (nevus, melanoma, seborrheic keratosis, lentigo NOS, lichenoid keratosis, solar lentigo, and café-au-lait-macule). The initial dataset had a significant class imbalance, a common issue when developing clinical AI: 32,542 images (98.00%) were labeled benign, while only 584 images (1.80%) were labeled malignant. This degree of imbalance requires special treatment because the conventional classifiers applied to such uneven datasets tend to lose a sensitivity associated with the malignant (minority) class to optimize overall accuracy. In order to avert this issue and to achieve fairness and predictive accuracy, targeted augmentation strategies were applied. This way, the two final trainings set balanced each other in size; for the purposes of this study, 5,000 images (2,500 benign and 2,500 malignant images) were used to train the models and this can be seen in Figure 1.

Figure 1: Class distribution chart

Regularization of the dataset involved the use of diverse essential preprocessing methods, such as lesion segmentation, resizing images to 600 by 600 pixels, and color normalization, to achieve uniform input quality prior to training. The purpose of color normalization was to standardize the appearance of the images, thereby minimizing variability introduced by differences in illumination and natural skin pigmentation.

Additional normalization and augmentation methods such as random rotations, horizontal/vertical flips, zoom and shift transformations and brightness/contrast adjustments were deployed specifically to enhance the model's robustness, ensuring that the EfficientNet-B7 could learn effective features from clean, consistent, and suitably generate varied image samples. This can be seen in Figures 2a and 2b.

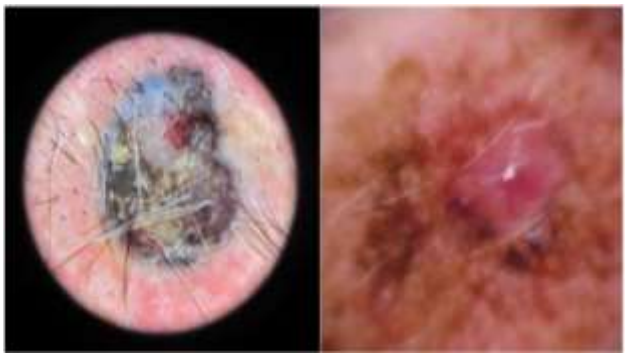

Figure 2a: Malignant images

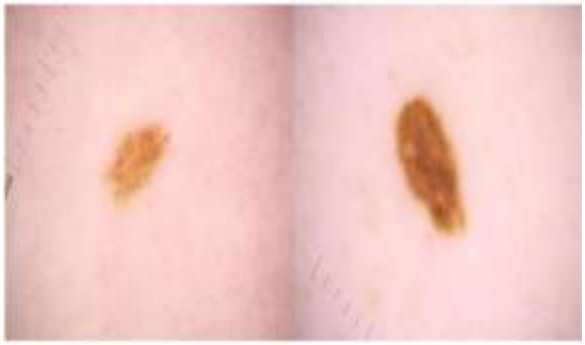

Figure 2b: Benign images

2.2 Feature extraction and classification

For this study, EfficientNet-B7 was utilized for feature extraction. The original top layers of the network were replaced for binary lesion classification. The extracted features were compressed through a layer implementing global average pooling, and a final output layer was responsible for producing a malignancy probability for each image. After fine-tuning EfficientNet-B7 on the preprocessed dermoscopic dataset, the extracted features were fed to a Radial-Basis Function kernel SVM for classification.

2.3 Training, validation and evaluation

We split the data with 60% for training and 40% for testing, while keeping class proportions intact. All cases were labeled as either "benign" or "malignant." The EfficientNet-B7 model was trained with the Adam optimizer for 50 epochs (learning rate 1e-4, batch size 32). Grid search cross-validation was used on the training set to determine the penalty parameter C and kernel γ of the SVM. The performance metrics included accuracy, specificity, sensitivity, F1-score, and AUC-ROC. We selected the model based on maximizing malignant sensitivity, while ensuring acceptable specificity, in line with clinical screening priorities.

3.0 Results and Discussion

The proposed hybrid model performed well in differentiating between benign and malignant cases on the test set. Overall accuracy reached 88.0%, with an AUC-ROC score of 88.63%, confirming its differential capability. For malignant lesions, sensitivity was very high at 99.0%, alongside a specificity of 87.0% and an F1-score of 93.0%. In contrast, the benign class demonstrated 95.0% specificity but lower sensitivity at 41.0%. Table 1 shows a summary of the training performance metrics.

Table 1: Key performance metrics

Metrics Class	Specificity (%)	Sensitivity (%)	F1-Score (%)	Accuracy (%)
Benign	95.00	41.00	58.00	88.00
Malignant	87.00	99.00	93.00	88.00

Figure 3 reflects a sensitivity trade-off as it relates to sensitivity. There were only 38 false negatives, with 545 false positives, which reflects a screening set of operating conditions, as it is more important that a cancerous lesion, which poses a threat, not be missed. Most importantly, it is seen that the sensitivity for a malignant lesion is 99.00%. It is clear from the analysis that our model is a highly sensitive screening tool compared to the previous architecture, which diminishes the possibility of hazardous false negatives, which is a critical characteristic in a cancer screening tool because, if a diagnosis is hazardous, it poses a more significant problem than a hazardous false positive. Although it meant a compromise on benign sensitivity, it is an acceptable compromise.

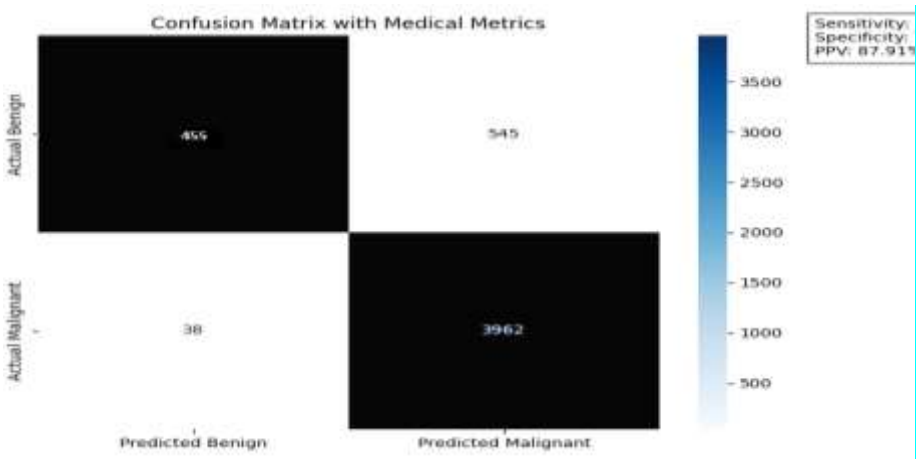

Figure 3: Confusion matrix and derived medical metrics

When we compared our model against the previous hybrid architecture, which used VGG16 and ResNet50, our model showed clear superiority, especially in the critical malignant classification. As shown in Table 2, our model achieved a higher F1-score for malignant cases (93.00%versus 91.00%). This improvement validates that the strategic use of EfficientNet-B7's fine grained feature extraction, combined with the Radial Basis Function (RBF) kernel SVM's robust classification power, provides a better solution for reliable clinical screening.

Table 2: Comparative performance (proposed model vs. prior model [Ghosh et al., 2024])

Model	Class	Specificity (%)	Sensitivity (%)	F1-Score (%)
VGG16+ResNet50	Benign	92.00	45.00	61.00
	Malignant	85.00	98.00	91.00
EfficientNet-B7+SVM	Benign	95.00	41.00	58.00
	Malignant	87.00	99.00	93.00

In respect to the prior VGG16+ResNet50 hybrid, the EfficientNet-B7+SVM model achieved higher values for malignant-lesion detection. It reached about 99% sensitivity, 87% specificity, and a 93% F1 score. In practice this means the model identifies almost all true cancer cases (very few false negatives). These gains translate to far fewer missed melanomas, making the model much more reliable for clinical screening, since missing a cancer is far more dangerous than a false alarm. This can be seen in Figure 4.

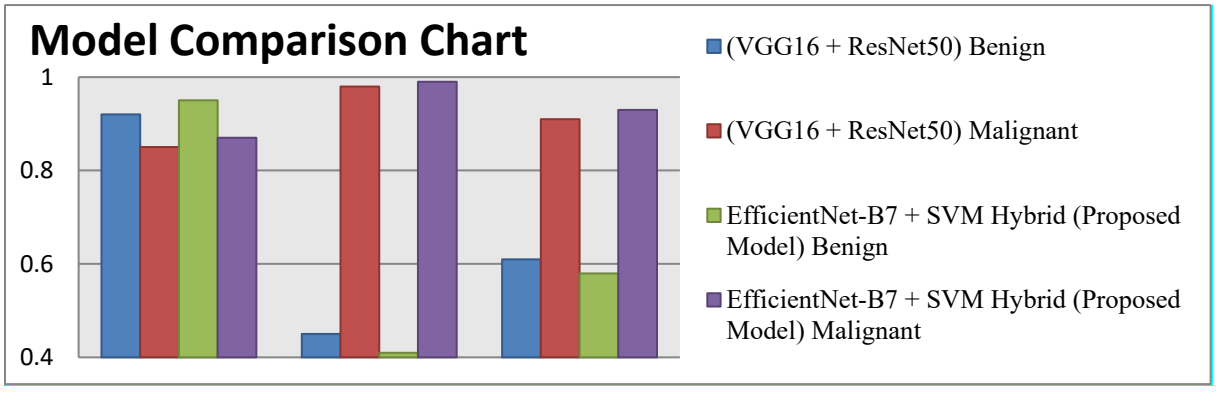

Figure 4: Comparative analysis chart of the proposed hybridized model

4.0 Conclusion

The new EfficientNet + SVM model represents considerable progress over the one developed by Ghosh *et al.,* (2024) that utilized VGG16 and ResNet50. The opportunity for missing a cancer case is minimized by concentrating on the identification of malignant cases. Specifically, the model showed an improvement of 99.00% (1% false negatives) in sensitivity for melanoma compared to the previous system. This is a direct result of EfficientNet-B7 providing improved feature representation, and the SVM providing better classification in latent space.

The design of this system is most suited to the screening of skin cancers with a high sensitivity, as illustrated by the malignant F1 score and sensitivity. From a clinical standpoint, this implies there are few, if any, missed cases of melanoma. The compromise is an increase in false positives (benign sensitivity is lower), but for the purpose of cancer detection, this is a necessary trade-off. For the continued improvement of this system, increased size and variety of datasets, adjusting model thresholds, and incorporating other explainable AI strategies (such as Grad-CAM and LIME) are all strategies to increase the clinical utility and reliability of the system.

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