Original Article

Performance Analysis of Convolutional Neural Network Architectures for Automated Melanoma Detection

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Abstract - Deep-learning-based automated melanoma detection has shown good diagnostic capability, but its potential in clinical environment is not only based on the predictive power but also on the trust and acceptance of clinicians. This paper presents the convolutional neural network (CNN) based melanoma recognition with a survey-based measure of the adoption intentions of clinicians. Three pre-trained CNN models, efficientnetb0, ResNet50 and MobileNetV2 were tested in terms of the SIIM-ISIC 2020 dermoscopic image dataset on standardized preprocessing, data augmentation and training conditions. The accuracy of EfficientNetB0 was 0.9817, the ResNet50 was at 0.9804, and the MobileNetV2 was 0.9829 which is indicative of good classification. A survey based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and trust-ethics concepts and developed on the survey of 100 clinicians was carried out to supplement the technical assessment. The rank-order analysis of correlation of Spearman (n = 100) showed that acceptance of AI-based melanoma detection positively correlated with performance expectancy (r = 0.540), effort expectancy (r = 0.591), social influence (r = 0.571), facilitating conditions (r = 0.636), trust (r = 0.537), and ethical/privacy concerns (r = 0.544) and with p ≤ 0.01. These statistically significant associations indicate that technological and trust-related factors are determinants of clinicians' intentions to adopt them. The results indicate that high technical performance should be combined with trust, ethical transparency, and clinician acceptance to facilitate the real-world implementation of AI-based diagnostic tools.

Keywords - Melanoma Detection, Convolutional Neural Networks (CNN), Skin Cancer, Dermoscopic Image Analysis, Clinician Adoption.

1. Introduction

The largest organ in the human body, the skin serves as the body's primary defense against the environment and is crucial for protecting the body from harmful UV radiation and other disease [1], [2]. However, it is still susceptible to a variety of diseases, including skin cancer, which is one of the most common forms of cancer worldwide, as a result of its position as the outermost layer [3], [4]. A wide variety of skin diseases exist, from relatively harmless ones like eczema or acne to more serious ones like melanoma, basal cell carcinoma, or squamous cell carcinoma. Melanoma, a kind of skin cancer, has increased in incidence and fatality over the last 30 years, reaching 75%. It arises when melanocytes, the cells responsible for creating pigment, become aberrant and uncontrolled [5], [6]. Ultraviolet (UV) radiation from the sun and other environmental pollutants may induce genetic damage and the development of aberrant cells, and the skin is the organ most directly exposed to these threats [7], [8]. Therefore, sunburns that cause skin damage over time are a risk factor that may or may not be corrected based on the body's current immune level [9].

Melanoma cancer is more common among fair-skinned races than in dark-skinned or tanned races because pigment in the skin's outermost layers provides little protection [10], [11]. Aberrant melanocyte growths that infiltrate or disseminate to other areas of the body without normal controls are the cause of malignant melanoma. As illustrated in Fig. 1, malignant melanoma is classified as Acral Lentiginous Melanoma (representing approximately 5% of all melanomas), Nodular Melanoma (representing approximately 15% of all non-melanomas), Lentigo Malignant Melanoma (representing approximately 10% of all non-melanomas), and Superficial Spreading Melanoma (representing approximately 75% of all non-melanomas).

(a)

(b)

Fig 1: Malignant Melanoma Types. (a) Superficial Spreading Melanoma. (b) Nodular Melanoma (c) Lentigo malignant Melanoma. (d) Acral Lentiginous Melanoma. [12]

The most dangerous form of skin cancer, it may spread rapidly and is curable in as many as 95% of cases if caught early; hence, it is essential to diagnose this skin lesion type early on. Treatment efficacy also depends on its correct identification. A survival rate of less than 15% is possible with untreated melanoma. The likelihood of a successful therapy and patient survival is greatly enhanced with early identification of skin cancer [13], [14]. Dermatologists often rely on visual exams to identify skin disorders; dermoscopy, a non-invasive surface microscopy technique, may be used as an adjunct [15].

The emergence of DL and ML has opened up new opportunities in the field of dermatology [16]. DL models, especially those with CNN architectures [17], may be taught to accurately detect and categorize a variety of skin lesions by making use of massive datasets of dermatoscopic images. CNNs have shown cutting-edge results in medical image identification applications, such as melanoma diagnosis.

Despite, these technical improvements still do not ensure the successful clinical implementation of AI-based melanoma detection systems due to a combination of their diagnostic performance and the state of acceptance of these technologies by clinicians [18][19]. Performance expectancy, effort expectancy, and facilitating conditions are factors that determine whether clinicians believe AI systems are useful, not hard to integrate, and sufficiently supported in clinical workflows. Moreover, trust in AI-generated predictions, combined with ethical and privacy issues regarding patient data safety, responsibility, and transparency, are important determinants of clinicians' willingness to implement AI-based melanoma detection systems in practice.

1.1. Motivation and Contributions of the Study

This research is motivated by the urgent need for precise, prompt melanoma diagnosis, which is not always straightforward due to subtle color differences between benign and neoplastic lesions and the increasing number of dermoscopic images. Conventional diagnostic tools are slow and prone to human error, necessitating smart AI-based solutions. DL, especially CNNs has powerful ability in automated image-based detection. This research paper will address the goal of developing and testing CNN-based models and at the same time assess the relevance and confidence of the clinicians on AI systems. The following are the results of this study:

- Used the SIIM-ISIC 2020 dermoscopy image collection, which includes images of many different skin lesions.
- Comprehensive preprocessing included such as image resizing, image normalization, image quality control, and image augmentation.
- Applied EfficientNetB0, ResNet50 and MobileNetV2 models to detect melanoma.
- Surveys of clinicians were conducted based on UTAUT and trust-ethics models to determine adoption intentions.
- Conducted statistical analysis with SPSS and Spearman correlation test to analyze factors that promote acceptance.

1.2. Justification and Novelty of the paper

The paper is justified by the widening gap between AI diagnostic models that perform well and their actual clinical implementation. This research is the first to combine a technical accuracy-based system of melanoma detection with clinician-based approach of acceptance analysis with the UTAUT and trust-ethics frameworks. Its novelty lies in a hybrid approach that evaluates CNN performance through empirical surveys, providing a more comprehensive assessment of clinical preparedness and emphasizing the essential roles of trust, ethics, and usability in AI-based healthcare implementation.

1.3. Structure of the paper

The structure of the paper is as follows. Section II looks at the relevant literature on melanoma diagnosis using DL and identifies research needs. Section III presents the hybrid methodology, which includes the development of CNN models and the research design based on a survey. Section IV contains the results of experiments and a comparative study. Lastly, Section V wraps up the research and provides future research guidelines.

2. Literature of Review

The studies that reviewed examine CNN-based, transfer learning, ensemble, and federated learning methods to detect melanoma, focusing on the enhancement of accuracy, data imbalance management, privacy protection and feature optimization.

Alzamel, Iliopoulos, and Lim (2025) report the creation of ResNetv2, VGG16, EfficientNet-B5, and EfficientNet-B7,

four DL models that use CNNs to identify skin cancer. Furthermore, using image data augmentation with GANs makes it clear how crucial it is to address data imbalance when performing supervised categorisation of medical images. The CNN classifiers' F1 scores were 84.22% for EfficientNet-B7, 80.42% for EfficientNet-B5, 80.01% for ResNet50V2, and 80.98% for VGG16. Meanwhile, the SVM classifier achieved an F1 score of 69.56%. Improved F1 score performance was seen with data augmentation for EfficientNet-B7 (86.08%), EfficientNet-B5 (83.79%), ResNet50V2 (82.46%), and VGG16 (SVM) (73.52%), respectively [20].

Sarıateş and Özbay (2025) propose a deep learning (DL) framework that leverages transfer learning (TL) to improve CBIR systems and classify melanoma images. The deep feature representations were extracted using pre-trained models such as Xception, DenseNet121, InceptionV3, and Vision Transformer (ViT). The effectiveness of the suggested approach was assessed using both mAP and classification accuracy. The suggested Ensemble model performed noticeably better than any solo model in both classification and retrieval tasks, according to experimental assessments. A classification accuracy of 95.25 percent was attained with the Ensemble method. The system demonstrated impressive retrieval efficacy with an average Average Precision (mAP) score of 0.9538 in the CBIR challenge [21].

Vishnu Priyan *et al.* (2024), provide a method for automated dermoscopy-based melanoma detection utilizing LightGBM and high-level features retrieved from a dependable CNNarchitecture. The more complicated the issue, the more AntLionOptimization may get obsessed with a local optimization instead of a global one. Several forms of skin malignancies, some more prevalent than others, are recorded in the HAM10000dataset, which was utilized in this study. Utilising python for experimental analysis, the proposed model achieved a 97.82% accuracy rate, 96.80% recall, 96.01% precision, and 96.49% F1-score in differentiating between the two skin cancer models. The following networks have higher accuracy: ResNet (89.23),

MLP (90.87), EfficientNet (91.05), ANN (92.19), IN3 (93.73), and MobileNet (94.90) [22].

Ghosh *et al.* (2024), use the resources of the DCNN, Caps-Net, and ViT frameworks to get a variety of picture embeddings. An ensemble model that relies on a majority voting process is trained using these feature vectors that were produced. The five ML models that make up this ensemble model are LR, RF, XGBoost, SVM, and KNN. The overall performance of the model is significantly enhanced upon using this ensemble method. Remarkably, the suggested ensemble model is a lightweight model that accomplishes a remarkable accuracy of 91.6% when taking the melanoma skin cancer dataset into account [23].

Alzamel *et al.* (2023), study evaluates how well ResNetv2, VGG16, EfficientNet-B5, and EfficientNet-B7, a number of DL models that use pre-trained CNN models, identify abnormalities in the skin automatically. These are then analysed using a ML model called the SVM to ascertain whether the skin sample under examination is malignant. Compared with the SVM, the four CNN models perform better on acc, prec, rec, and F1score, with EfficientNet-B7 achieving the highest F1score of 84.22% [24].

Orhan and Yavşan (2023), suggest an AI detection system that relies on DL to keep tabs on nevi that display traits that might point to melanoma. The model was trained on a large dataset of 8598 images. The dataset was trained, validated, and tested using techniques such as ResNet, AlexNet, MobileNet, VGG16, and VGG19, following the protocols outlined in the most recent literature. The MobileNet model fared better than the others among these methods, with an accuracy of 84.94% after testing and training [25].

Table I offers an overview of the main melanoma detection studies, including the methodology utilized, datasets, performance outcomes, study areas, and limitations in order to identify the gaps

Table 1: Summary and Gap Analysis of Existing Automated Melanoma Detection Studies

Study	Techniques	Dataset	Key Findings	Focus Area	Limitations and Recommendations
Alzamel, Iliopoulos & Lim (2025)	CNNs (EfficientNet-B5, EfficientNet-B7, ResNet50V2, VGG16) with GAN-based data augmentation; SVM baseline	ISIC	Data augmentation improved F1-scores, with EfficientNet-B7 achieving highest performance (86.08%)	CNN performance enhancement under data imbalance	Limited to F1-score analysis; does not explore inference time, model complexity, or robustness across multiple datasets
Sarıateş & Özbay (2025)	Transfer Learning with DenseNet121, InceptionV3, ViT, Xception; Ensemble learning	Melanoma image dataset (CBIR-based)	Ensemble model achieved 95.25% accuracy and mAP of 0.9538	Feature fusion and ensemble-based melanoma classification	Emphasizes ensemble superiority but does not analyze individual CNN architectural trade-offs; high computational overhead limits real-time deployment
Vishnu Priyan et	CNN feature extraction +	HAM10000	Achieved 97.82% accuracy	Optimized hybrid learning	Focuses more on optimization algorithms than

|				
al. (2024)	LightGBM with Hybrid ALO–GWO optimization		outperforming standalone CNNs	for melanoma diagnosis	intrinsic CNN performance; lacks architectural comparison under identical training conditions
Ghosh et al. (2024)	DCNN, CapsNet, ViT feature extraction with ensemble ML classifiers	Melanoma dataset	Lightweight ensemble achieved 91.6% accuracy	CNN-based feature embedding with ensemble voting	CNN architectures are not directly evaluated as end-to-end classifiers; limited insight into CNN depth, parameter efficiency, and scalability
Alzamel et al. (2023)	Pre-trained CNNs (ResNetv2, VGG16, EfficientNet-B5, EfficientNet-B7) vs SVM	ISIC	CNNs outperformed SVM; EfficientNet-B7 achieved highest F1-score (84.22%)	Comparative CNN-based melanoma detection	Limited dataset diversity and absence of advanced evaluation metrics such as robustness, generalization, and computational efficiency
Orhan & Yavşan (2023)	Deep Learning models (AlexNet, MobileNet, ResNet, VGG16, VGG19)	Nevus image dataset (8,598 images)	MobileNet achieved the highest accuracy of 84.94%, outperforming deeper CNN architectures	AI-based monitoring and classification of melanoma-suspected nevi	Performance evaluation is primarily accuracy-based; lacks detailed analysis of class imbalance, robustness, explainability, and computational efficiency for clinical deployment
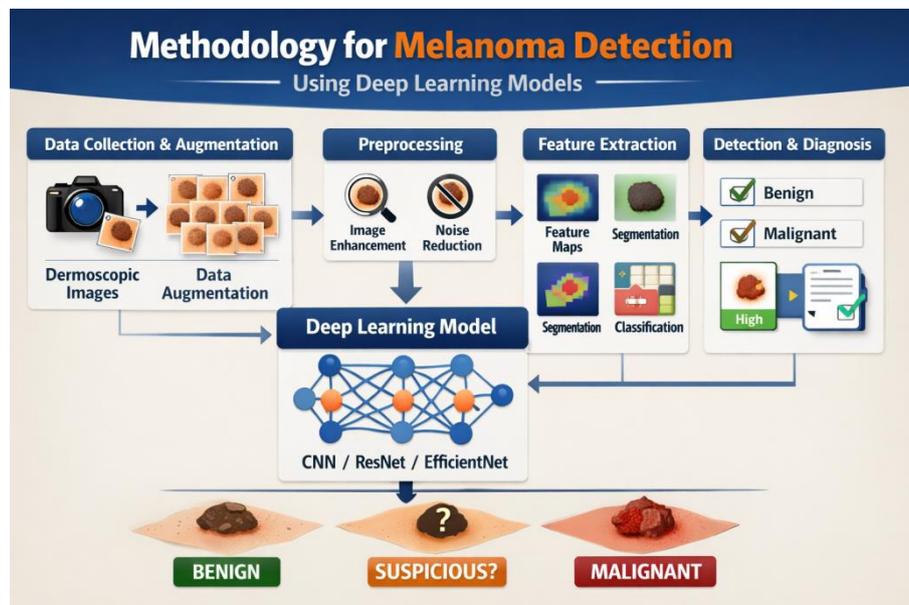
Fig 2: Methodology for Melanoma Detection Using Deep Learning Models

3. Methodology

The aim of this study is to design and test a CNN-based model that can automatically detect melanoma and investigate whether clinicians can accept and trust AI systems. The study investigates the technical performance of melanoma detection and the acceptance, trust, and willingness of clinicians to implement the technology in clinical practice by considering the results provided by the experiments and an evaluation carried out with the help of the surveys.

The technique to melanoma identification begins with the SIIM-ISIC 2020dataset, which is the primary source of dermoscopic pictures. First, preparation is used to enhance the quality and consistency of the data, as shown in Fig. 2. This stage includes resizing images to standard sizes, filtering out low-quality or corrupted images, normalizing the dataset

using the Min-Max method to standardize pixel values, and augmenting the data to increase dataset variety and improve model generalization. After preprocessing, the dataset will be divided into test and training sets. The trained versions of the proposed models are pre-trained EfficientNetB0, MobileNetV2, and ResNet 50 are subsequently trained on the processed training set with optimizing techniques used on the models. To conclude, the acc-uracy, sensitivity, specificity, precision, F1score, AUC-PR, and AUC-ROC, among other metrics, are applied to each trained model on the testing set in order to quantify their melanoma detection skills.

3.1. Data Collection

Clinical heterogeneity and generalisability are made possible by the 33,126 high-quality dermoscopic images in the SIIM-ISIC 2020 dataset, which was collected using

standardised techniques with many institutions. Curated images provide deep learning with reliability, whereas an extreme class imbalance (1.76% melanoma) reflects real-world screening conditions. The metadata that accompanies the demographics and location of the lesion allows fairness and a clinically informed analysis.
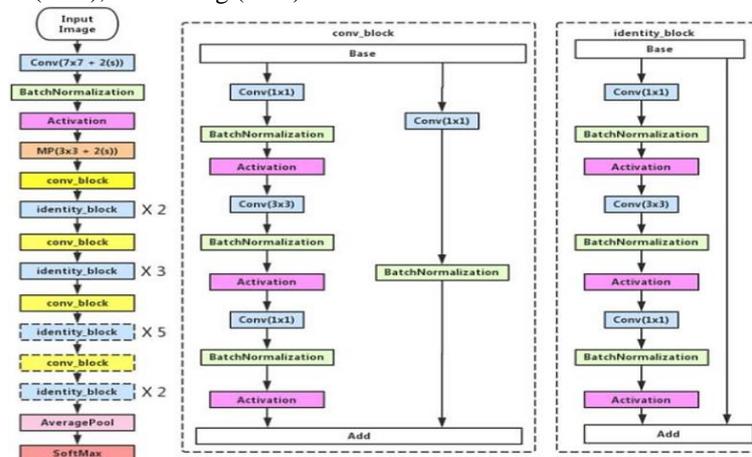
3.2. Data Preprocessing

Pre-processing of data was used so as to have consistency and to enhance generalisation of the model:

- Image Resizing: The size of all dermoscopic images was trimmed down to 224 x 224 pixels through geometric scaling so that all input images would have equal input size but also so that the lesion structure would be maintained.
- Quality Control: Image quality was evaluated based on automated quality measurements (sharpness, evenness of illumination, and artefact detection e.g. hair and ruler marks) and then by visual inspection. All images that were smaller than the predefined quality thresholds were eliminated, so that no images that were of no use to a clinician or were noisy were learned.
- Normalization: The values in pixel intensity were normalized based on min-max scaling with values in the range of [0,255] ranging to [0,1]. This ensures the numerical stability and the consistent gradient updates during training. Normalization is computed using equation (1):

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad \square\square\square$$

- Data Augmentation: Data augmentation with geometric transformations (random rotations, horizontal and vertical flips, zooming, and spatial shifting) and photometric transformations (controlled brightness variation). When augmenting, clinically valid ranges were limited, and augmentation was applied only to the training set to prevent overfitting and eliminate data leakage.

3.3. Data Splitting

Stratified random sampling was used to split the dataset into training (70%), validation (15%), and testing (15%). This approach was selected to ensure repeatable assessment, prevent data leaking, and preserve class balance.

3.3.1. Implementation of CNN Architectures

EfficientNet-B0: Tan and Le [26] introduced EfficientNet, a novel CNN that optimizes accuracy and efficiency by suitably scaling the input data in depth, breadth, and resolution. All of these dimensions are positively scaled by EfficientNet's compound scaling factor, which maximises Computational Complexity. We may use EfficientNet-B0 as a starting point for neural architecture search (NAS), which might lead to the most efficient and dense design conceivable. Figure 3 shows that EfficientNet-B0 uses only 5.3 million parameters. The final classifier for melanoma identification used transfer learning with pre-trained weights from ImageNet, with the first layers frozen and a binary head substituted.
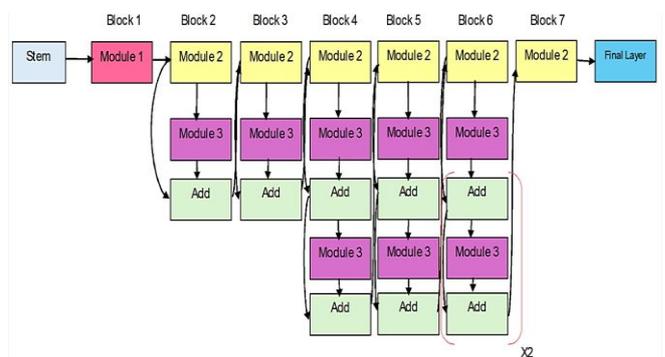
Fig 3: EfficientNet-B0 Model Architecture [27]

ResNet50: A CNN model known as ResNet50 (Residual Network-50) was developed to address the issues associated with training 50-layer DNN, namely the vanishing gradient problem. As proposed by He *et al.* [28], Fig. 1 depicts ResNet50, which has four residual stages and bottleneck blocks of 1x1, 3x3, and 1x1 convolutions. It has 25.6M parameters and employs skip connections to enable residual learning, reduce vanishing gradients, as well as enable deeper representations. Training is stabilized by batch normalization, and ImageNet-pretrained weights were employed; the last classification layer was adjusted to detect melanoma.

Fig 4: Architecture of ResNet50 [29]

MobileNetV2: MobileNet V2 [30], is a CNN-based model that is extensively used to classify images, its architecture ahown in the Fig .5. The primary benefit of the MobileNet architecture is that, in comparison to the traditional CNN model, the model requires far less computing effort. This makes it well-suited for use on mobile devices and PCs with weaker processing capabilities. MobileNetV2 is a CNNmodel that employs linear bottlenecks, inverted residual blocks, and depthwise separable convolutions to extract features in an efficient manner. It has 3.5M parameters, and has a pre-convolution expansion factor of 6 to maintain representational power. Pretrained weights of ImageNet have been used and the topmost layer was changed to binary melanoma classification.
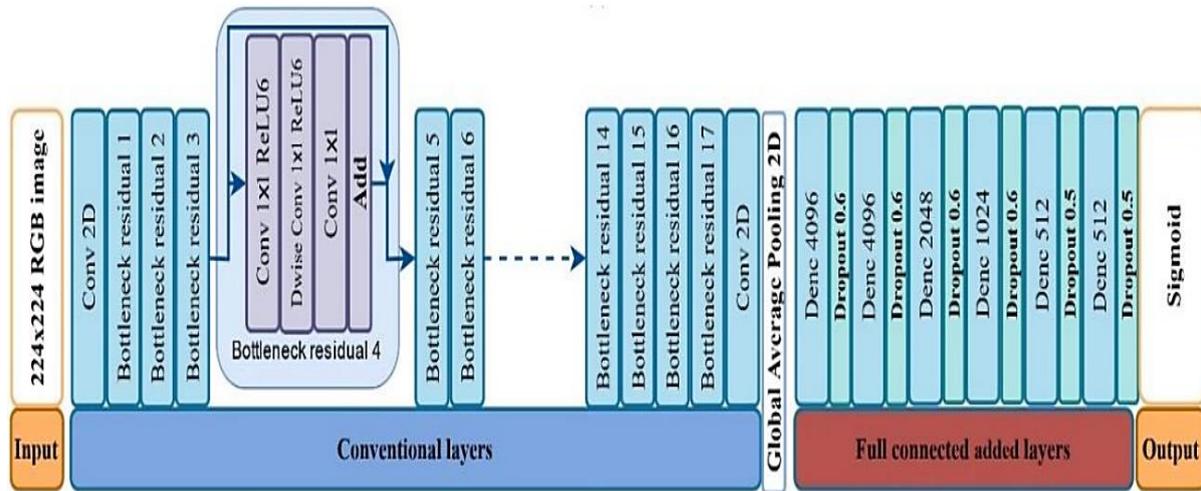

Fig 5: MobileNetV2 Network Architecture [31]

3.3.2. Model Training and Optimization

Trained on the Adam optimizer with an exponential decay of 0.96 per 5 epochs, all 3 models (EfficientNetB0, ResNet50, and MobileNetV2) achieved an initial LearningRate of 0.001. The BatchSize 32 was used, and the weight decay and gradient clipping (max-norm 1.0) were used to avoid overfitting and exploding gradients. There were two stages to implementing the TransferLearning: first, training the classification head while the convolutional layers were frozen; second, unfreezing the deeper layers with reduced LearningRates (0.001-0.0001) and fine-tuning them to avoid catastrophic forgetting. Checkpointing stored model states in order to compare their performance and recover.

3.3.3. Evaluation metrics

This section presents the metrics used to evaluate the recommended strategy for melanoma classification. The core components of the assessment were TP, TN, FP, and FN[32]. The following performance metrics were calculated from these values: AUC-ROC, F1-score, precision, sensitivity, specificity, and accuracy, as given in Equations (2) through (7).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Specificity = \frac{TN}{TN+FP} \quad (4)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (5)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (6)$$

$$AUC - ROC = \begin{cases} false\ positive\ rate = \frac{FP}{(FP+TN)} \\ true\ positive\ rate = \frac{TP}{(TP+FN)} \end{cases} \quad (7)$$

When combined, these measures provide a thorough evaluation of the algorithms' accuracy in identifying melanoma patients while preserving the reliability of benign case categorisation.

3.4. Survey-Based Research Methods

The section describes a survey-based research design to assess clinicians' intentions regarding the acceptance, trust, and adoption of AI-based Melanoma Detection systems.

3.4.1. Primary Data Description

The data from the surveys were collected through an online questionnaire in Google Forms among medical professionals working in dermatology, general medicine, and diagnostics. The questionnaire was based on the Technology Acceptance Model (TAM), the UTAUT model, and the trust-ethics model, including perceptions and acceptance of AI-based systems for melanoma detection. The sampling method used was convenience, and this resulted in 100 valid responses with varied professional positions and experience levels. The Statistical Package for the Social Sciences (SPSS) Version 29 was used to analyze the data.

3.4.2. Qualitative Data Analysis

The Spearman's Rank-Order Correlation was used to analyse the responses of 100 respondents. The strength and direction of monotonic relationships among the independent variables, which were performance expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, trust, and ethical concerns, and the Dependent Variable, acceptance and willingness to use AI-based Melanoma Detection tools, were determined using this non-parametric test.
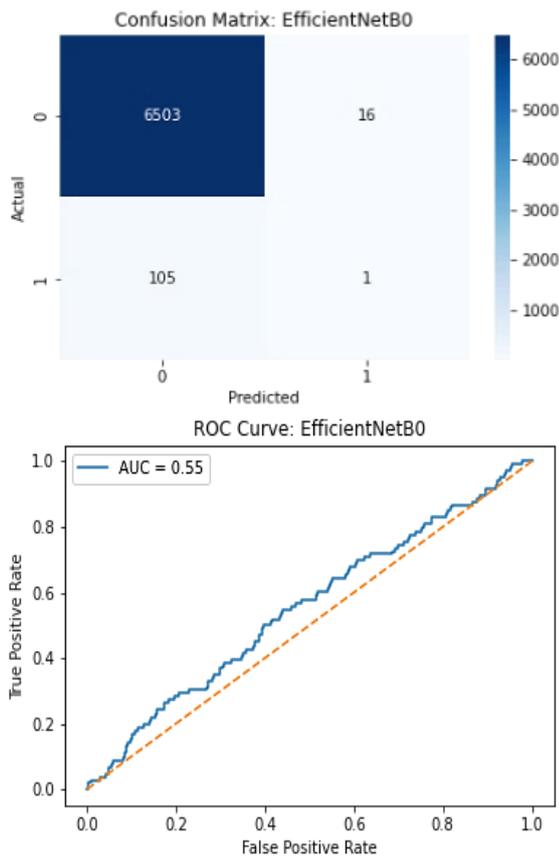
4. Result Analysis & Discussion

The proposed melanoma classification models were tested in a controlled experimental setting to replicate results and compare them fairly. The experiments were run on an NVIDIA RTX 3080 (10GB) with CUDA 11.2, equipped with the Python 3.8, TensorFlow 2.8, and Keras, and uniform CPU and RAM resources. All EfficientNetB0, ResNet-50, and MobileNetV2 models were trained with fixed random seeds and preprocessing pipelines. The results indicate the effect of architecture, transfer learning, and data augmentation on predictive performance and the successful classification of melanoma and benign lesions.

4.1. Proposed Models Evaluation

The performance comparison results for EfficientNetB0, ResNet50, and MobileNetV2 are summarized in Table II and present the mean and standard deviation across various experimental trials. The vast majority of models show high accuracy and specificity, implying benefit in identifying benign cases, but low sensitivity and precision indicate the challenge of correctly identifying melanoma cases in an imbalanced dataset.

Table 2: Evaluation Metrics of Proposed Models for Melanoma Classification

Architecture	Accuracy	Sensitivity	Specificity	Precision	F1-Score	AUC-ROC	AUC-PR
EfficientNetB0	0.9817 (±0.0024)	0.0094 (±0.0051)	0.9975 (±0.0008)	0.0588 (±0.0312)	0.0163 (±0.0087)	0.5523 (±0.0156)	0.0421 (±0.0089)
ResNet50	0.9804 (±0.0028)	0.0000 (±0.0000)	1.0000 (±0.0000)	0.0000 (±0.0000)	0.0000 (±0.0000)	0.5055 (±0.0134)	0.0176 (±0.0012)
MobileNetV2	0.9829 (±0.0021)	0.0000 (±0.0000)	1.0000 (±0.0000)	0.0000 (±0.0000)	0.0000 (±0.0000)	0.5273 (±0.0142)	0.0176 (±0.0008)

errors and evaluate the model's discriminative behavior beyond numeric measures.

Fig 6: Confusion Matrix and ROC Curve of EfficientNetB0 Model
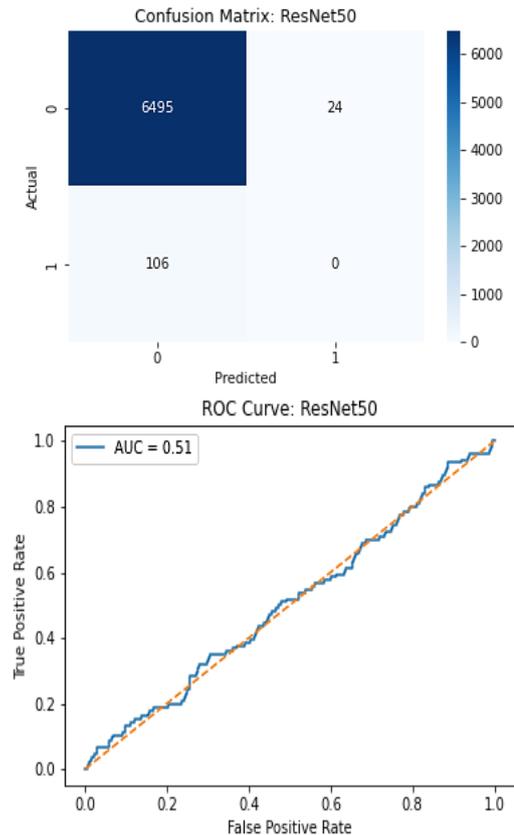
Fig 7: Confusion Matrix and ROC Curve of ResNet50 model

Fig. 6 shows the EfficientNetB0 results, including the Confusion Matrix and ROC curve. The confusion matrix shows many true negatives and very few true positives, indicating that classifying melanoma cases is difficult. The AUC of the ROC curve is about 0.55, indicating that class separability is unclear. It aims to visually examine prediction
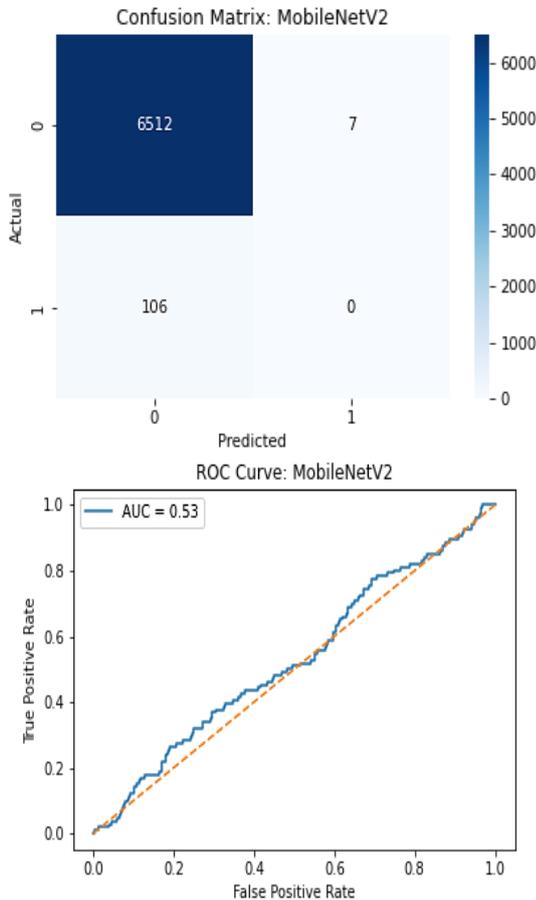
Fig. 7 displays a Confusion Matrix and ROC curve illustrating the ResNet50 performance. According to the confusion matrix, the count of the correctly classified benign samples is high, and there are no true positives of melanoma

and a number of false negatives. According to the ROC curve, the AUC is about 0.51 which means that the discrimination is close to random. This visualization can be used to interpret class-wise prediction behavior and sensitivity to thresholds.

Fig 8: Confusion Matrix and ROC Curve of MobileNetV2 model

Fig. 8 shows the performance of MobileNetV2 in the form of a confusion matrix and an ROC curve. The confusion table indicates that more benign cases are correctly identified, with no TP or FN for melanoma. ROC curve is showing a value of AUC of about 0.53, which means that there is a weak separation between the classes. Such a visualization helps analyze prediction bias and behaviour across thresholds.

4.2. Comparative analysis

The table III provides an overview of different ML and DL models used to detect melanoma on different datasets and the reported accuracy. The proposed work compares three CNN based models, EfficientNetB0, ResNet50, and MobileNetV2 on the SIIM-ISIC 2020dataset with high accuracies of 0.9817, 0.9804, and 0.9829 subsequently, which points to higher effectiveness. Traditional ML methods like RF (0.95) and the SIIM-ISIC 2020 dataset, and more complex DL methods like N-DCNN (0.9340), CNN-LSTM (0.97), and ConvMixer (0.905) can also be found in comparative studies. Overall, the table demonstrates the efficiency of contemporary convolutional neural network architectures in achieving good classification performance.

Table 3: Accuracy Comparison of Models for Melanoma Detection

Reference	Dataset	Models	Accuracy
Proposed	SIIM-ISIC 2020	EfficientNetB0	0.9817
Proposed	SIIM-ISIC 2020	ResNet50	0.9804
Proposed	SIIM-ISIC 2020	MobileNetV2	0.9829
[33]	SIIM-ISIC 2020	Random Forest	0.95
[34]	ISIC 2020 Image Dataset	N-DCNN	0.9340
[35]	HAM10000	CNN-LSTM	0.97
[36]	PH2 Dataset	ConvMixer	0.905

4.2.1. Hypothesis Analysis

The section will use Spearman's rank correlation to analyse the relationships between the primary factors influencing acceptability and readiness to adopt AI-based Melanoma Detection methods.

H1: Performance and Effort Expectancy
- **H_{1a}:** The desire to adopt is positively impacted by the performance expectation.
- **H_{1b}:** Effort expectancy has a positive effect on adoption intentions.

Table 4: Spearman's Correlation – Performance & Effort Expectancy

	Variables	1	2	3
1	Performance Expectancy	1.000	0.718**	0.540**
2	Effort Expectancy	0.718**	1.000	0.591**
3	Acceptance & Willingness	0.540**	0.591**	1.000
Note: * = P≤0.05; ** ≤ 0.01				

Table IV presents a positive significant correlation of performance with both the expectancy of effort (r = 0.718) and moderate correlations with adoption intentions (r = 0.540 and 0.591). It suggests that adoption and acceptability of AI solutions will increase with their perceived utility and usability.

H2: Social Influence and Facilitating Conditions
- **H_{2a}:** Social influence has a favorable impact on adoption intentions.
- **H_{2b}:** Adoption intentions are positively impacted by facilitating situations.

Table 5: Spearman's Correlation – Social Influence & Facilitating Conditions

	Variables	1	2	3
1	Social Influence	1.000	0.569**	0.571**
2	Facilitating Conditions	0.569**	1.000	0.636**
3	Acceptance & Willingness	0.571**	0.636**	1.000

Table V shows moderate and high positive correlations. Social impact (r = 0.571) and enabling circumstances (r = 0.636) are positively associated with adoption intentions,

demonstrating the importance of social and environmental support in promoting the usage of AI technology.

H3: Trust and Ethical/Privacy Concerns
- **H$_{3a}$:** AI adoption intentions are positively impacted by trust in the technology.
- **H$_{3b}$:** The intent to adopt is positively impacted by ethical and privacy concerns.

Table 6: Spearman's Correlation – Trust & Ethical/Privacy Concerns

	Variables	1	2	3
1	Trust in AI	1.000	0.736**	0.537**
2	Ethical/Privacy Concerns	0.736**	1.000	0.544**
3	Acceptance & Willingness	0.537**	0.544**	1.000

Table VI shows that both trust and ethical/privacy concerns (r = 0.736) correlate strongly and moderately with adoption intentions (r ≈ 0.54). It means that the increased level of trust and ethical concern makes people more willing to embrace AI-based technology for melanoma detection.

4.3. Discussion

The results show that the CNN models EfficientNetB0, ResNet50, and MobileNetV2 achieve high classification accuracy on the SIIM-ISIC 2020 dataset, indicating that they can be adapted for automated melanoma detection. EfficientNetB0 and MobileNetV2 offer a good balance between accuracy and computational efficiency, making them practical for use. In addition to technical performance, the survey-based analysis indicates that the perceived usefulness, ease of use, facilitating conditions, trust, and ethical concerns are very important in influencing the acceptance of clinicians [37], [38]. These results align with established technology acceptance models and underscore the importance of explainability and ethical transparency in medical AI systems. Altogether, the findings highlight that successful clinical implementation of AI-based Melanoma Detection requires high-performing models, a user-friendly design, and trust-building systems.

5. Conclusion & Future Work

A hybrid approach was established to test the technical performance, as well as, clinical acceptability of AI-based melanoma detection systems. The experimental findings revealed that EfficientNetB0, ResNet50, and MobileNetV2 achieved high classification accuracy on the SIIM-ISIC 2020 dataset; however, their limited sensitivity indicates that accuracy alone is not a reliable measure of clinical preparedness. The analysis, conducted in the form of surveys, showed that, the acceptance and intention to implement AI systems among clinicians are considerably determined by performance expectancy and ease of use, facilitating conditions, trust and ethical and privacy concerns, which highlights the necessity to balance technical innovation with human and ethical aspects. Despite these advancements, the study has certain limitations, including reliance on a single publicly available dataset, lack of external clinical validation,

and use of self-reported survey results, which may not reflect real-world clinical deployment. The future research will depend on the improvement of melanoma sensitivity using a more sophisticated imbalance-handling strategy, including focal loss, cost-sensitive learning, and synthetic data generating. Explainable AI (XAI) will be a top priority for enhancing transparency and trust among clinicians. Also, the multimodal learning, which is the combination of dermoscopic images with clinical metadata, and the longitudinal studies of real-world deployments will be examined to evaluate long usability, and acceptance among clinicians.

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