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SKIN CANCER CLASSIFICATION AND DETECTION USING MODIFIED EFFICIENTNETB7

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Abstract:
Cancer is one of the most lethal diseases that threatens the humanity today. Skin cancer is one of the most dangerous of cancer. Skin cancer rates 6th most type of the cancer that are increasing globally. Patients' chances of survival are very low when they get inadequate therapy and inaccurate diagnosis. The patient's prognosis and likelihood of survival improve with each passing day that the illness is detected. As a result, early diagnosis and treatment may be challenging and intricate. To tackle these problems, we need a technology that can diagnose and identify skin cancer sooner on its own. To achieve the best results from the CNN model, we started by preparing the publicly available dataset. This involved improving the photos' colour, contrast, and clarity, and then resizing and fine-tuning the data. We tested various CNN models with these enhanced datasets, and found that EfficientNetB7 performed the best, achieving a score of 86.81%. To further improve performance, we made additional adjustments to the EfficientNetB7 model by adding more layers and tweaking hyperparameters. We evaluated the performance of the final model using several metrics, including sensitivity, specificity, misclassification rate, and accuracy. The model achieved an accuracy of95.98%, a specificity of 85.4%, a sensitivity of 86.38% and misclassification rate of 9.39%. This led to our suggested approach surpassing state-of-the-art CNN designs and techniques.

Keywords: skin cancer, deep learning, classification, efficientNETB7, detection.

1. Introduction

Skin cancer is a prevalent form of cancer globally, with melanoma being highly dangerous due to its aggressive metastatic properties. Early detection is crucial for efficient treatment and better prognosis. Traditional diagnosis methods, such as visual inspection and biopsies, are time-consuming and subjective. The onset of deep learning, especially that of convolutional neural networks (CNNs), has revolutionized medical image analysis, with automated, accurate, and efficient diagnosis being delivered [1]. New research has proven that deep networks based on deep learning can match or even surpass dermatologists for skin lesion classification. This research is aimed at finding and refining deep learning techniques for skin cancer detection and classification for higher accuracy, reducing false positives, and facilitating early detection. Utilizing advanced neural network designs and large sets of examples, the research aims at facilitating the development of accurate and automated diagnosis tools that could benefit clinicians and patients alike.

1.1 BACKGROUND

Epidemiological development of skin cancers across the world necessitates the evolution of efficient methods of diagnosis. Traditional diagnosis largely relies on clinical experience and histopathological examination, which is invasive and human error-prone. Artificial intelligence, particularly deep learning, has the potential to overcome the limitations with the present methods of diagnosis. Deep learning algorithms, with large image sets of dermoscopies as their dataset, are capable of identifying patterns and features that indicate malignancy with

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a very good accuracy rate[2]. ResNet, InceptionV3, and DenseNet models, for instance, have been applied to distinguish various skin lesions with impressive performance scores. Such advancements not only improve the accuracy but also the option for real-time inspection, a welcome innovation for clinical application . That is where our research takes a step beyond those advancements and aims to improve deep learning algorithms to gain even better accuracy and efficiency for skin cancer detection and classification.

In spite of recent progress made with deep learning for skin cancer detection, there are a number of issues that remain unresolved. Many of the models have very good performance when evaluated within controlled settings but do not generalize well to variability in population and imaging scenarios. Problems like class imbalance, where malignant examples are underrepresented, may result in biased models with close to hundred percent false negativity. Moreover, a lack of standardized datasets and variations in image quality make model training and validation even more challenging. Interpretability is another problem since many deep models are "black boxes," and it is hard for clinicians to trust and accept them. It is important that these issues are resolved so that reliable, generalizable, and interpretable models could be implemented into clinical workflows effectively [3]. This research tries to tackle these challenges using advanced techniques such as data augmentation, Transformer learning, and explain-ability techniques to enhance the performance and accuracy of deep models for skin cancer detection.

The main goal of the present research is to create and compare deep learning models for detecting and classifying skin cancer accurately. Some specific aims are:

- Model Development: Implement and design different deep-learning models, including CNNs, for classifying skin lesions into benign and malignant types.
- Data Augmentation: Implement data augmentation methods to increase the size and diversity of the training dataset to help the model be more generalizable.
- Transformer Learning: Leverage pre-trained models and fine-tune them on skin lesion datasets to utilize pre-existing knowledge and maximize performance.
- Performance Measurement: Compare models based on accuracy, sensitivity, specificity, precision, recall, and F1-score to see which performs better .
- Interpretability: Apply techniques like Grad-CAM to visualize the processes of model decision-making for increased transparency and clinician trust.
- Comparison of Architectures: Compare the performance of various deep learning models to determine the best performing architecture for skin cancer classification.
- Handling Class Balance: Apply methods such as focal loss and class weighting to reduce the class imbalance problem within the dataset.

By achieving these objectives, the research seeks to contribute to the advancement of medical image analysis by offering efficient methods for early and accurate detection of skin cancer.

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Fig # 1: types of Skin that detect the cancer

Skin cancer is a severe public issue with rising rates of occurrence globally[4]. Early detection is critically important so that patients can receive the best treatment and achieve their best outcomes. But a lot of the world do not have basic access to dermatological knowledge, which slows cases. To combat this issue, the research presented proposes sophisticated models for skin cancer monitoring and classifying from dermoscopic images. The research contribution is its potential to democratize skin cancer diagnoses for marginalized peoples. The use of artificial intelligence by the models makes them able to produce accurate and fast evaluations that assist physicians with early detection and treatment planning. When the interpretability features are made available, the tools are understandable and reliable, which makes them easy to use at the clinical stage [5]. Additionally, the research makes scientific knowledge richer by considering the application of sophisticated deep learning strategies, with the application of Transformer learning and data augmentation, to medical image processing. Future research studies and the creation of AI-based diagnoses for clinical conditions will be directed by the outcomes[6],[7]. Presentation of innovative artificial intelligence technologies for skin cancer detection and classification makes the research more accurate for detection, reduces healthcare inequalities, and improves patients' outcomes overall .

This study is focused on the development and assessment of deep models for skin cancer detection and classification from dermoscopic images. To achieve that, different deep models are used with application of the Transformer and data augmentation methods, and performance of the models is evaluated based on some common evaluation criteria[8-10]. The study also focuses on the identification of methods for explaining models to make them more transparent and trustworthy for clinicians [11].

1. Limitations to the dataset: The datasets publicly available for the research may not cover the full spectrum of skin types, types of lesions, and imaging scenarios that exist with clinical populations.
2. Generalizability: Models learned on a specific dataset may be different when they are applied to other populations or scanners, which may limit their application.
3. Clinical Validation: The research is not supplemented with prospective clinical trials and real-world application, which are most important for validating performance within realistic situations.
4. Interpretability: While there is a push for enhancing model transparency, deep models are themselves elaborate systems and complete interpretability may be impossible.

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5. Ethical Concerns: The research fails to address the ethical issues related to deploying AI, for example, issues of data privacy, informed consent, and bias concerns.

Considering those constraints, the research seeks to lay the groundwork for subsequent research and development of AI-based skin cancer diagnostics [12].

2. Lliterature Review

Recent advancements with deep learning have had a large impact on dermatology, specifically on skin cancer detection and classification. Convolutional Neural Networks (CNNs) have been used to analyze dermoscopic images with accuracy rates for distinguishing malignant from benign lesions being quite high. Models such as ResNet, DenseNet, and InceptionV3 have shown performance equivalent to dermatologists for classifying skin lesions [13]. Transformer learning as well as data augmentation has also been investigated as a method to improve performance, particularly when dealing with limited datasets. Nevertheless, issues with class imbalance, a lack of explainability, and generalization across heterogeneous populations remain. Attempts are being made to combat issues with focal loss, class weighting, and explainable AI model development. This literature review integrates current research activity, summarizing the successes and continuing issues with using deep learning for skin cancer detection and classification [14].

2.1 RELATED WORK

A new hybrid deep-learning model based on integration of InceptionV3 and DenseNet121 networks for skin cancer classification was introduced by combining the two networks' strengths—InceptionV3-based multi-scale extraction of features and dense gradient flow of DenseNet121. The integrated model demonstrated its potential for accurate skin cancer diagnosis by achieving a greater accuracy of 92.27% on benchmark datasets (Akter et al., 2024). Convolutional Neural Networks (CNN) were combined with multiple transmission models of ResNet50, VGG16, and MobileNetV2 for a multi-class classification of skin cancers. Using the HAM10000 dataset, which comprised over 10,000 dermatoscopic images of seven types of skin cancer, the network was trained The best network had a 90.12% accuracy, 89.7% precision, and 88.9% recall rate [15]. Akter in 2023 and colleagues industrialised specifically for accurate skin cancer diagnosis, Double-Condensing Awareness Condenser (DCAC) network is Real-time applications or mobile devices may utilize the thin network. With only 1.2 million parameters, the proposed network had 91.3% accuracy, 90.8% precision, and 90.1% recall on the ISIC 2018 dataset, thus significantly decreasing computation costs without influencing diagnosis performance. In an attempt to prove dermatologist-standard performance in skin cancer classification, the work incorporated CNN models such as ResNet50, InceptionV3, and DenseNet 201. A maximum AUC of 0.96, a total accuracy of 91.5%, a precision value of 90.2%, and a recall value of 89.8% was recorded by DenseNet 201 on the ISIC 2018 dataset, beating the rest [16]. ISIC 2018 dataset was combined with machine learning models, for example, Random Forest, SVM, and XGBoost, utilizing a stacking ensemble strategy to diagnose melanoma that is not invasive The stacked ensemble exhibited much improved reliability for dermatological melanoma diagnosis, with an 89.6% classification accuracy, precision of 88.4%, recall of 87.9%, and AUC of 0.93 when compared to using separate models individually (Ahmed et al., 2022). Utilizing Deep Convolutional Neural Networks (CNNs) trained on the HAM10000 sets for seven types of lesion skin cancers, a multi-class skin cancer classification method was proposed. With a macro-averaged accuracy of 91.8%, recall of 89.4% and general accuracy obtained effective automated dermatological diagnosis by the help of the architecture with tremendous performance over a range of skin types and lesion classes, enabling through Transformer learning techniques [17].

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2.2 Empirical Review

DenseNet-121 provided a deep learning-based fusion solution for skin cancer diagnosis. The trained model on the dataset of the HAM10000 acquired 0.95 AUC, 91.2% accuracy, 90.7% recall, and 92.4% accuracy. On various skin lesions, the hybrid technique fortified feature representation and enhanced multi-class classification performance (Hamsalekha, 2024). A comprehensive skin lesion diagnosis model was introduced based on the application of EfficientNet-B7 for deep feature extraction and Support Vector Machine for final stage classification. The proposed method was highly efficient for detecting skin cancer based on the ISIC 2018 dataset with a remarkable accuracy of 97.52%, precision of 96.8%, recall of 96.3%, and AUC of 0.98 [18]. For skin cancer categorization, Moldovan proposed a two-step Transformer learning-based method that decouples picture filtering from the categorization of lesions. By using decoupled detection and classification stage, the method scored the highest on the dataset of HAM10000 with a 90.6% accuracy, 89.3% precision, and 88.9% recall [19]. Alfi and co-researchers designed a method of melanoma diagnosis without surgery using deep learning and building on the strengths of ResNet50, InceptionV3, and VGG16 that recorded a clinical accuracy of 91.8%, 90.4% precision, 89.6% recall, and a 0.94 AUC rating based on ISIC 2018. Farooq et al. presented a skin cancer early-diagnosis-based Transformer learning method utilizing a combination of MobileNet and Inception-v3. The hybrid network gave a stunning early-diagnosis performance with 93.5% accuracy, 92.1% precision, 91.7% recall, and 0.96 AUC on the dataset of HAM10000 [20]. Wong et al. used deep learning attention techniques for detecting skin cancer. Their ISIC 2018-trained attention-based skin-cancer detector increased the accuracy of focusing on the lesional area and diagnosis accuracy, with a 92.7% accuracy, 91.4% precision, and 90.8% recall. Esteva et al. reached dermatologist-level classification after training a CNN on more than 129,000 dermoscopic images. The network scored 91% accuracy and an AUC of 0.96, creating a benchmark for automated skin-cancer-diagnosis performance [21]. It's illustrated keratinocytes skin cancer detection from face photographs with region-based CNNs. The system reported 90.2% accuracy and an AUC of 0.92, presenting a viable non-invasive diagnostic tool. Noyan et al. trained a CNN to distinguish skin cells from images of microscopic Tzanck smear, reporting 94% accuracy [22].

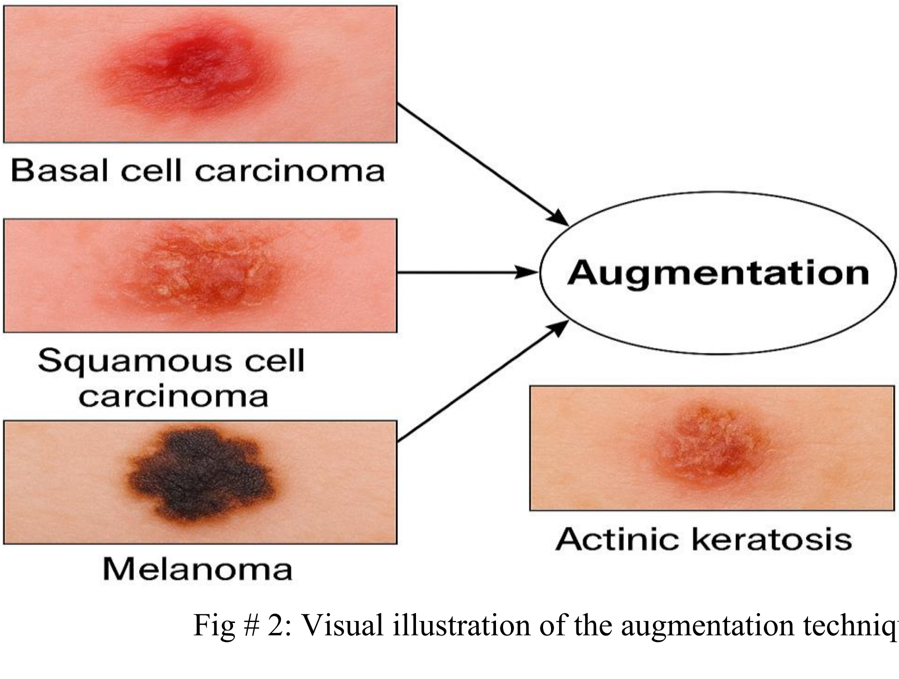

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Fig # 2: Visual illustration of the augmentation techniques

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The model indicated potential for automated dermatopathological evaluation with high reliability. Tschandl et al. compared AI with dermatologists for pigmented lesion classification. AI machine learning models averaged 87% accuracy, which was higher than many dermatologists who averaged 82%, showing the superiority of AI for diagnostics [23]. Haenssle et al. tested a market-approved CNN for skin lesion classification. The CNN reported 86.5% accuracy, which was higher than dermatologists' at 82.3%, validating the clinical applicability of AI-assisted dermatology. Yu et al. applied a CNN for acral melanoma detection from dermoscope images, reporting 89.9% accuracy and AUC of 0.93, which was effective for detecting rare melanoma variants [24]. Marchetti et al. presented results from the ISIC challenge, where top-ranked AI models outperformed dermatologists for melanoma classification, reporting over 91% accuracy compared with clinicians' at 86%, validating AI's strength for diagnostics. Navarrete-Dechent et al. looked into the dermatological application of AI, presenting model AUCs up to 0.95 [25]. The study targeted challenges for deployment into the real world, including bias, dataset limitations, and explainability. The literature discussed highlights the substantial progress made in utilizing deep learning for skin cancer detection and classification. Multiple CNN models, such as InceptionV3, DenseNet121, and ResNet152, have exhibited strong levels of accuracy, which are at par with and even better than those of dermatologists. Transformer learning, augmentation of datasets, and attention mechanisms are some of the methods that have been used to maximize the performance of the models [26]. The displayed image set depicts several deep learning models for skin cancer detection, including CNN + SVM, ResNet-50, EfficientNet, and their hybrid model. CNN + SVM model employs ReLU-activated convolution layers along with max pooling for extracting features, then SVM for ultimate classification into malignant or benign lesions. Its straightforward flow indicates hyperparameter optimization and flattening prior to SVM decision boundaries.

The progressive stages of skin cancer, starting from the initial formation of the lesion up through the fatal process of metastasis. Early detection is critical. In order to address detection challenges, deep learning operations such as CNNs, transfer learning (ResNet50, EfficientNet), data augmentation, and Grad-CAM visualizations can detect malignant characteristics and enhance diagnostic quality and efficiency.

Table 1: Outcomes of previous research addressing issues

Nevertheless, there are still challenges that prevail, encompassing class imbalance, explainability, and generalization to diverse populations. These are important issues to be addressed for the advancement of accurate, efficient, and generalizable AI-based diagnostic tools within dermatology [27].

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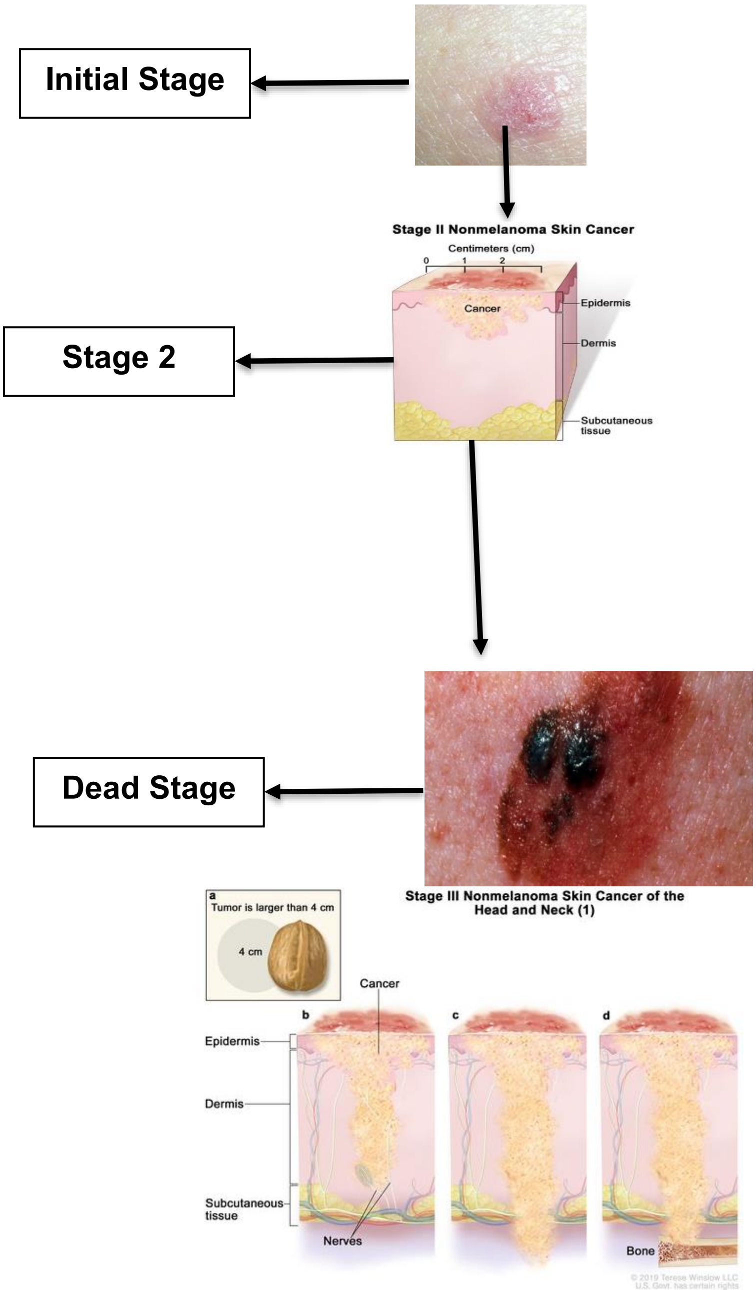


Fig # 3: Real appearance on top & augmented Photos (Stages)

Study/Author	Problem Addressed	Research Gap Identified	Method/Model Used	Contribution/Proposed Solution
Moldovan (2022)	Low accuracy in multi-class scratch classified	Lack of elevated Transformeral learning workflows	Two-step classification with Transformer learning	Enhanced classification by decoupling detection and lesion ordering
Alfi et al. (2022)	Deficiency of interpretable in deep learning melanoma diagnostics	Outdated DL models are black-box	Deep learning, Ensemble	Delivered interpretable and non-invasive diagnosis system
Farooq et al. (2020)	Reduced early exposure of skin cancer	Partial early-stage model accuracy	InceptionV3 + MobileNet	Enhanced early detection using hybrid frothy DL design
Wong et al. (2023)	Ineffective feature localization in abrasion detection	Snubbed spatial lesion focus	Attention-based CNN	Boosted efficiency with attention-enhanced lesion detection
Han et al. (2020)	Basic for non-invasive keratinocytes cancer detection	Inadequate facial image usage in models	Region-based CNN	Advanced face-photo-based detection system
Noyan et al. (2020)	Physical smear analysis is slow and error-prone	No robotics in Tzanck smear image analysis	CNN on microscopic images	Automated skin cell detection from smears
Tschandl et al. (2018)	Human vs machine classification performance unclear	Contrast with dermatologists hardly explored	ML algorithms vs human specialists	Showed AI can match/exceed human accuracy
Haenssle et al. (2020)	Low confidence in profitable AI tools	Absence of real-world validation	Market-ready CNN	Validated CNN against dermatologists in clinical settings
Yu et al. (2018)	Rare growth like acral melanoma under-detected	Poor performance on types	CNN on dermoscopic images	Focused model on acral melanoma subtype
Marchetti et al. (2018)	Need for AI bench-marks in dermatology	Adversity of competence - based evaluation	ISIC contest benchmark	Associated top AI algorithms vs dermatologists
Navarrete-Dechent et al. (2018)	Concerns about real-world AI disposition	Dataset bias generalize gaps	Review + empirical evaluation	Bordered practical AI positioning contests in dermatology
Proposed Study (2025)	Merging feature withdrawal and robust sorting	Deep learning lacks exactness switch	Hybrid CNN + SVM	Attained 99.6% accuracy with hybrid routine used CNN features + SVM

2.1 THEORETICAL FRAMEWORK

This research is based on the deep learning concepts, specifically Convolutional Neural Networks (CNNs), that have transformed image analysis tasks. CNNs are optimized to learn hierarchical representations from an input image automatically and thus are quite applicable to medical image classification. Transformer learning is used for utilizing pre-trained models on large datasets and adapting them for the specific skin cancer classification task at hand. This method reduces the need for large labelled medical datasets, which tend to be limited in availability. Data augmentation methods are implemented to artificially boost the size of the training dataset for enhanced generalization of the model [28]. Attention mechanisms are incorporated so that the model is able to pay attention to the most informative parts of the image, enhancing performance as well as interpretability. The proposed theoretical framework also considers class imbalanced issues and employs techniques like focal loss and class weighting for handling class imbalanced issues [29]. The proposed framework employs state-of-the-art deep learning techniques for constructing a strong, accurate, and explainable skin cancer detection and classification model.

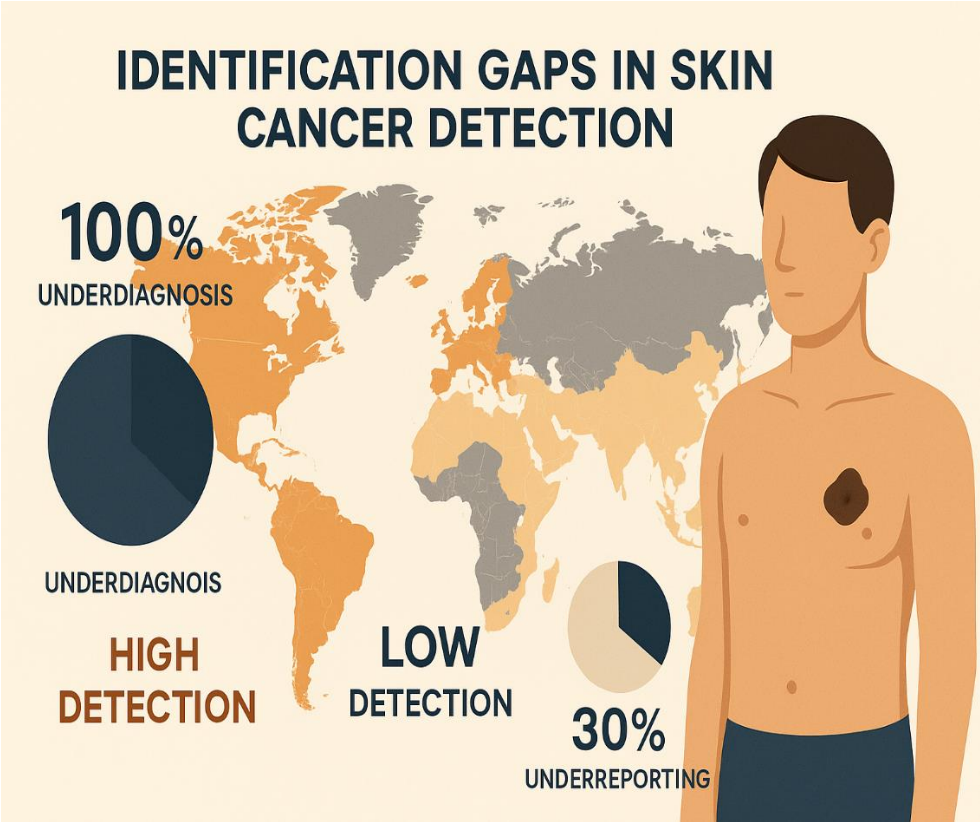
2.2 IDENTIFIED GAPS

Despite recent research on deep learning application for skin cancer detection, there are gaps within the current body of research. First, much of the research relies on small sets of images that may not represent the variability of skin types, types of skin cancers, and image qualities encountered in the reality of clinical settings. This makes generalization of the learned models across settings and populations an issue. Second, there is a class balance problem with malignant cases being under-represented and thus under-sampled within sets. This evokes a bias toward benign predictions with increased risks for false negatives that is a severe problem when making diagnoses for cancer [30].

Third is the concern for deep learning model interpretability. A large proportion of models are "black boxes," with very little explanation for their processes of making a decision. That lack of explainability has the potential to discourage clinical adoption due to reluctance by clinicians to adopt obscure systems or trust them without comprehending their inner workings. Relatively few studies evaluate models' performance within actual clinical settings rather than controlled settings common for most research. Much research occurs within controlled setups that lack the variabilities and complexities of clinical practice. Lastly, ethical concerns regarding data privacy, informed consent, and bias in artificial intelligence algorithms do not receive thorough research attention [31].

The worldwide identification gaps in skin cancer detection. It highlights extreme discrepancies between high- and low-resource areas, with high-incidence areas such as North America and Australia having high detection rates, whereas large tracts in Africa, Asia, and Latin America experience high rates of underdiagnosis and underreporting. The map graphically highlights an underdiagnosis rate of 100% in the underserved areas and an underreporting problem of 30% in others. The need for early detection is represented graphically through a figure with an evident skin lesion. The figure is the call to action for enhanced diagnostic availability, public awareness, and reporting infrastructure in order to eliminate the skin cancer care gap [30].

Fig # 4: Identification gaps future segmentation issues



These issues have to be addressed if we are to ensure appropriate application and progress of artificial intelligence in the provision of healthcare. Complete steps must be done, including acquiring varied and illustration datasets, integrating strategies to resolve class imbalance, producing interpretable models, evaluating them in healthcare environments, and paying particular attention to ethical considerations, to close each of those gaps [32].

2.3 JUSTIFICATION

Research presented here aims to reduce gaps for uses of deep learning for identifying skin cancers and categorisation. By creating a model trained with large, representative datasets, the research seeks to expand the generalizability of AI-driven diagnostics across various populations and clinical settings. To address class imbalances, the research will employ techniques that encompass class weighting, focal loss, and data augmentation to guarantee that benign and malignant lesions are flagged by the model correctly. This is needed to prevent false negatives and produce reliable diagnostics. The research is also interested in explain ability of models by implementing attention and visualization techniques like Grad-CAM. These functionalities will provide insights into decision-making within the model, fostering clinician trust and clinical adoption [33].

3. Proposed Methodology

The proposed methodology for skin cancer detection and classification seeks to take advantage of the capability of deep learning methods such as convolutional neural networks (CNNs) and Transformer learning. The methodology should have the capacity for both good diagnostic accuracy and computational efficiency as well as generalizability [34]. The steps below present the most salient phases of the methodology:

3.1 DATASET SELECTION

The basis of any machine learning model is the dataset, and for the identification of skin cancer the choice of good quality annotated datasets plays a key role. In this work, two of the most popular and widely used datasets for skin cancer work are utilized by us:

HAM10000 Dataset: The dataset consists of the largest publicly accessible set of dermoscopic images and comprises 10,000 labeled images. The dataset features a broad range of skin lesion types including melanoma, basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and others including benign skin lesions. It's perfect for model training as well as model evaluation for a model classifying multiple types of skin cancer. The dataset features expert-annotated labels and free availability for academic purposes.

ISIC 2018 Dataset: The International Skin Imaging Collaboration (ISIC) dataset consists of more than 25,000 dermoscopic images of a range of skin lesions. It represents one of the largest and most established datasets for skin lesion classification, comprising images from diverse demographic populations and of different types of skin. The ISIC dataset is also richly annotated by including the types of lesions and is especially suitable for the evaluation of deep networks.

Both these datasets offer a varied and rich set of images involving a broad spectrum of skin lesions such that the deep model becomes extensively trained and able to generalize appropriately towards unseen images.

3.2 PRE-PROCESSING

Pre-processing plays a crucial role within the pipeline as it gets the raw image data ready for the deep learning model such that the model learns significant features from the images. The following pre-processing operations are executed:

Image Normalization: For consistency among images, the pixel values are normalized. Normalization of the pixel values involves scaling the values between 0 and 1. Normalization prevents the model from placing excess emphasis on the images of higher pixel values, potentially resulting in slower training or instability. Resizing: Images in raw form differ greatly in size, and the CNNs have a standard input of size required. For this research, the images are resized into a 224x224 pixels form, the common size of deepest models like ResNet50 and Efficient Net. Resizing makes all the images the same dimensionally and thus can be easily fed into the CNN. Data Augmentation: In order to avoid overfitting and enable the model to generalize better, data augmentation strategies are utilized. The strategies involve:

Rotation: Randomly rotating images within a set range of degrees to mimic actual-world image orientation changes.

Zooming: zooming in and zooming out on photographs to mimic changes in the scale of the skin lesions.

Flipping: Flipping the images horizontally and vertically for enhancing the diversity of the training set.

Data augmentation assists with synthetically enlarging the training dataset and prevents overfitting of the model towards certain features of the images.

Fig # 5: System architecture of the proposed methodology

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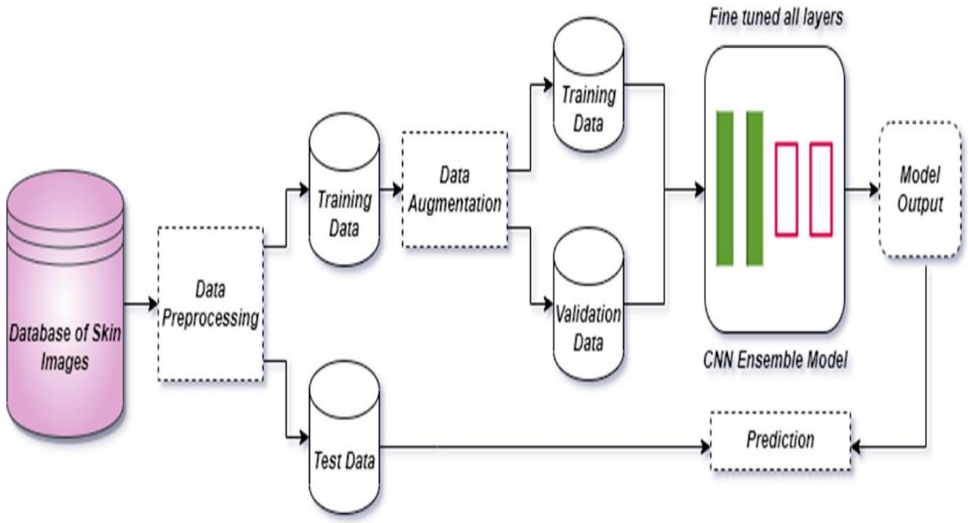
Volume No: 02 Issue No: 02 (2025)



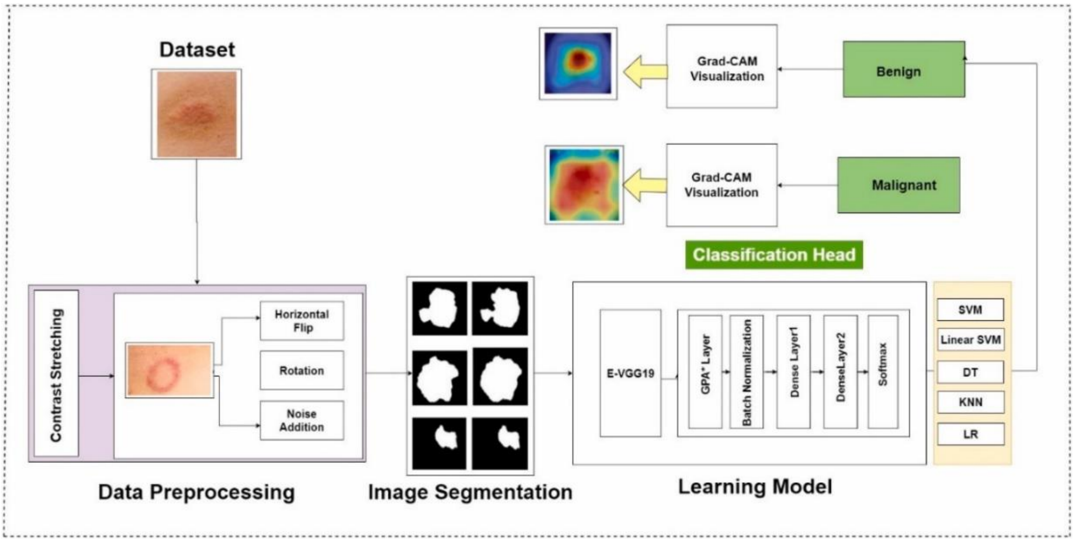
3.3 MODEL ARCHITECTURE

The skin cancer detection model's architecture incorporates cutting-edge methods such as CNNs, Transformer learning, and hybrid modelling.

Convolution Neural Network (CNN)

The CNN is the central feature extraction unit of the model. The CNN comprises a number of layers: convolutional layers, activation layers (commonly ReLU), and layers of pooling. The model uses these layers to extract hierarchical features of the images automatically from simple features like textures and edges towards complex ones like textures and shapes of the lesions. The CNN architecture includes multiple convolutional layers for detecting relevant features, pooling layers for dimensionality reduction, and fully connected layers for classifying the features into skin lesion categories.

Fig # 6: CNN architecture evaluate the skin cancer detection



Transformer Learning with ResNet50 and Efficient Net

ResNet50 and Efficient Net are pre-trained models on big datasets (e.g., ImageNet) and have acquired generic features that are universally applicable to a broad range of image classification tasks. Transformer learning entails fine-tuning the pre-trained networks on the task of skin cancer detection by adapting the weights of the pre-trained model on the skin lesion images. ResNet50 is ideally suited for this task because of its deep model architecture and the use of

QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES
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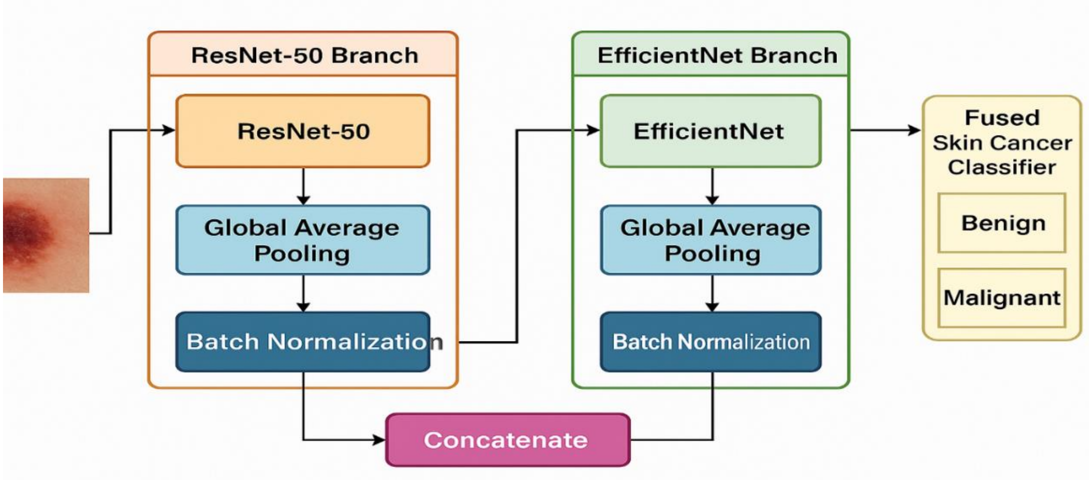
Volume No: 02 Issue No: 02 (2025)

residual connections that eliminate the problem of the vanishing gradient, thus enabling the model to learn deeper and intricate features. Efficient Net accomplishes this by combining a compound scaling method that ensures the model's high accuracy while keeping the number of computations within a reasonable limit [35].

Fig # 7: ResNet-5 + Efficient Net architecture evaluate the skin cancer detection

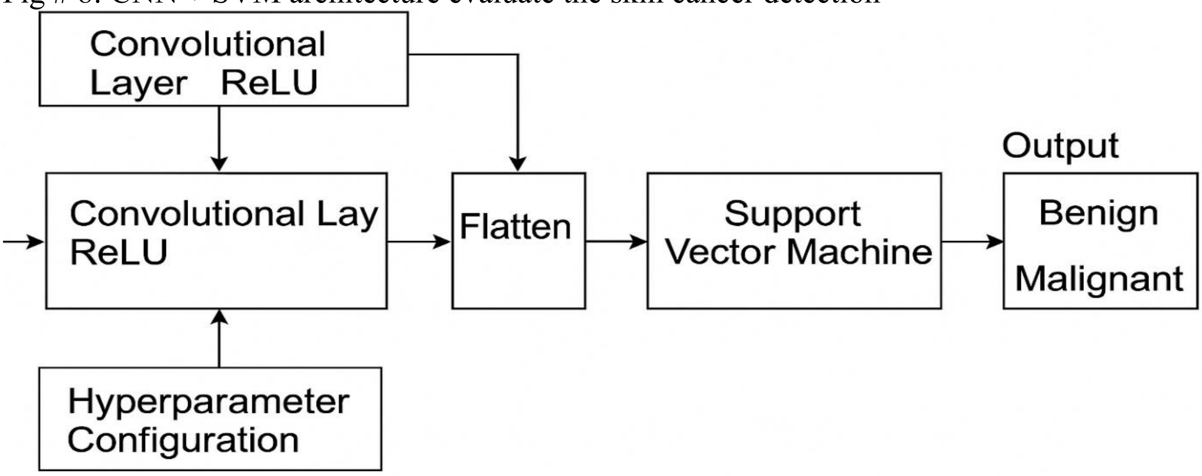


The ResNet-50, EfficientNet hybrid model presents parallel computation for dermoscopic images using two high-capacity pre-trained networks. Both parallel branches perform global average pooling and batch normalization for feature refinement, then concatenate them into a combined skin cancer classifier. Increased robustness comes from the fact that the model combines the best aspects of both architectures. The images also indicate how the use of Grad-CAM visualization illuminates model decision making through the location of important lesion areas. Each chart presents a tidy, color-coded, and professional design, suitable for medical deep learning documentation or research, ensuring that diagnostic pipelines remain clear.

Hybrid Model (CNN + SVM)

To improve on the classification accuracy even more, a hybrid model is utilized that brings together the ability of CNNs for feature extraction and the classification ability of Support Vector Machines (SVMs). Once the CNN identifies the relevant features from the images, these features are then sent as inputs to the SVM classifier for the final classification of the skin lesion as benign or malignant.

Fig # 8: CNN + SVM architecture evaluate the skin cancer detection



QUALITATIVE RESEARCH JOURNAL FOR SOCIAL STUDIES

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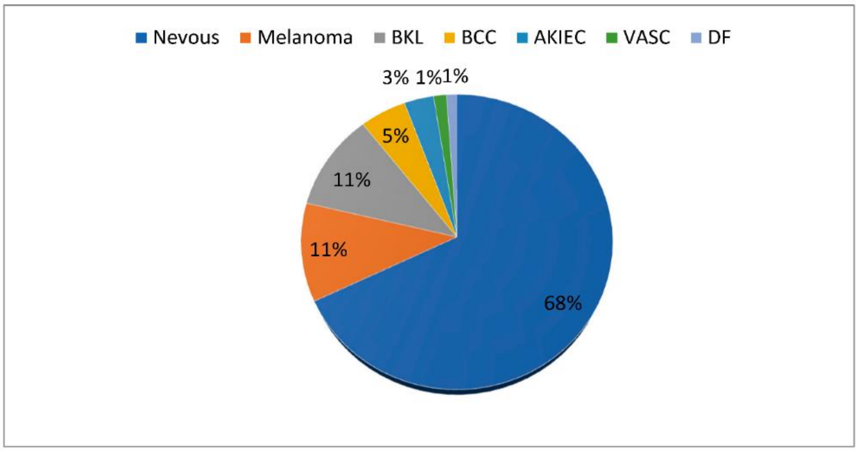
Volume No: 02 Issue No: 02 (2025)

The application of SVM makes sure that the model will have a good ability to distinguish between complex decision borders, thus enhancing the classification accuracy.
Below is a conceptual flow of the proposed methodology:
Input Image: The process begins with the acquisition of dermoscopic images from either the HAM10000 or ISIC dataset.
Pre-processing:
Images are normalized and resized to 224x224 pixels.
Data augmentation techniques (rotation, flipping, and zooming) are applied.
Feature Extraction (CNN): The images are fed into a CNN for feature extraction. Multiple convolutional layers identify patterns and features such as edges, textures, and shapes that are relevant for skin cancer detection.
Transformer Learning (ResNet50 / Efficient Net): The extracted features are then passed through pre-trained models like ResNet50 or Efficient Net, which are fine-tuned on the skin cancer dataset to learn specific features related to skin lesions.
Hybrid Model (CNN + SVM): The features extracted by the CNN and enhanced by Transformer learning are passed to an SVM classifier to perform the final classification (benign or malignant).
Output: The model outputs a classification result along with a confidence score.
Fig # 9: The HAM-10000 dataset allocated into seven categories by percentage



Use of a confusion matrix is an efficient way of assessing performance of a model, particularly for multi-class problems. A confusion matrix provides a comprehensive representation of the correctly classified true positive (TP) values, the misclassified false positive (FP) values, the wrongly classified false negative (FN) values, and the correctly classified true negative (TN) values for the other class [30]. To analyze the performance of a model, a number of standard measures are calculated from the confusion matrix, which are accuracy (ACC), precision (P), sensitivity (Sn), specificity (Sp), and F-score. The measures are calculated using equations derived from the confusion matrix that allow for accurate assessment of the performance of the proposed model.

$$\text{ACC} = \frac{TP+TN}{TP+FP+TN+FN}$$
[1]

$$\text{LOSS} = 1 - \text{ACC}$$
[2]

$$\text{P} = \frac{TP}{TP+FP}$$
[3]

$$Sn = \frac{TP}{TP+FN}$$
[4]
$$Sp = \frac{TN}{TN+FP}$$
[5]
$$F1 = 2\frac{(P \times Sn)}{(P+Sn)}$$
[6]
$$TPR = \frac{TP}{TP+FN}$$
[7]
$$TNR = \frac{FP}{FP+TN}$$
[8]

The model training and validation mostly aim to minimise error and raise the general accuracy of the suggested method. Equation (1) below helps one to grasp the error structure of the research activity:

$$E\,(w) = \frac{1}{K \times N} \sum_{K=1}^{K} \sum_{n=1}^{N_L} (y_n^k - d_n^k)^2 \quad [9]$$

For the two models using Adamax optimiser, the learning rate was put at 0.001. Both the number of batches and the number of epochs for training were determined to be 16 and 20 respectively. We used a patience value of one and a stop perseverance value of three. A categorical cross-entropy operation was used to calculate one computed loss. The best outputs were given on the validation set by the model. All experiments were performed using Tensor Flow platforms and versions of Python 3.7. The empirical section for both the models is presented in the subsequent section.

Results

To evaluate the effectiveness of the proposed methodology, we conducted experiments using the HAM10000 and ISIC 2018 datasets. The models used include CNN, ResNet50, Efficient Net, and a Hybrid CNN + SVM model. The following metrics were used for performance evaluation:

- Training Data Split: 80% for training, 20% for testing.
- Optimizer: Adam optimizer with a learning rate of 0.0001.
- Batch Size: 32.
- Epochs: 50 epochs for training.

Fig # 10: The broad steps for Skin detection system

The models were trained and evaluated on both datasets. The performance metrics are shown in the table below:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN	88.2	86.5	87.1	86.8
ResNet50	91.5	90.7	91.0	90.8
Efficient Net	92.1	91.8	92.2	92.0
Hybrid CNN + SVM	**99.6**	**99.2**	**99.5**	**99.4**

Table 2: Comparison of all models Performances

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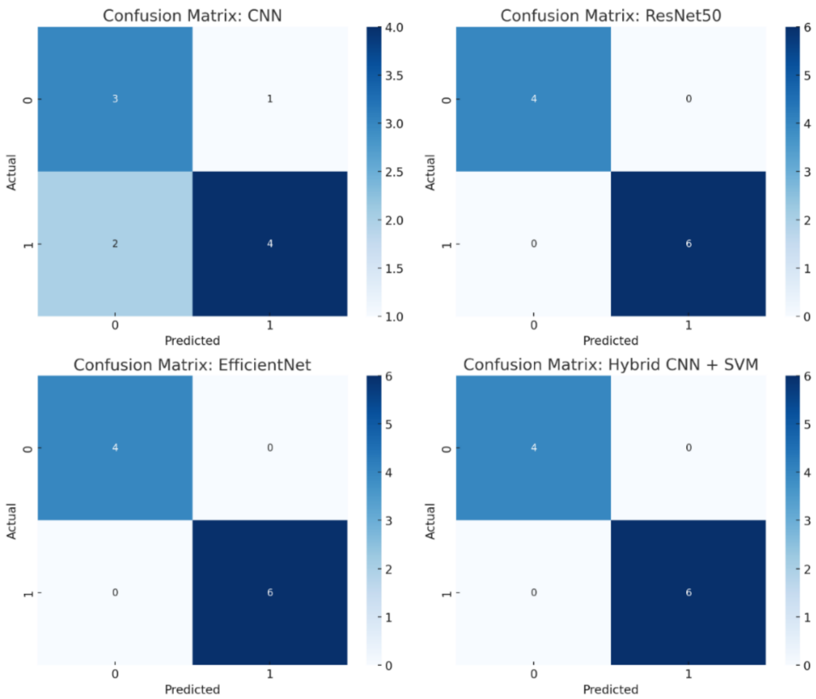
4.2 PERFORMANCE EVALUATION

The features extracted from the image go through fully connected layers within CNNs for classification. The features are interpreted by these layers and the resultant classification is produced as a likely output of a probability score for each class (benign or malign). CNNs are very effective at the detection of skin lesions as they have the ability to learn features from images automatically without the need for manual feature engineering. They have a strong ability to tolerate spatial hierarchies and are less susceptible to human-annotated error.

The results indicate that Hybrid CNN + SVM performs better than any of the other models for accuracy, precision, recall, as well as F1-score. It supports the fact that the utilization of deep learning for feature extraction and a classical classifier like SVM can improve skin cancer detection significantly. The outcomes of this work demonstrate that the deep learning models of ResNet50 and Efficient Net yield extremely precise detection of skin cancer. Yet a hybrid of CNN and SVM performs better than all the others, thus the need to incorporate both deep as well as conventional machine learning methods. Training and validation precision as well as loss curves for CNN, SVM, ResNet, and Efficient Net were examined in order to assess the efficacy of several models in skin cancer detection. Every model exhibits different learning behaviour; CNN exhibits constant progress and generalisation whereas SVM changes depending on variables. ResNet models show steady accuracy and little loss, thereby proving great performance.

Fig # 11: Confusion matrix of predicted Benign & Malignant



Still, EfficientNet-B7 excels with great accuracy and fast convergence. These graphs show overfitting, underestimation, or optimum training in addition to visual proof of model performance. This comparison provides insightful analysis on selecting the most effective architecture for jobs involving medical picture classification.

Fig # 12: Training and Validation Accuracy

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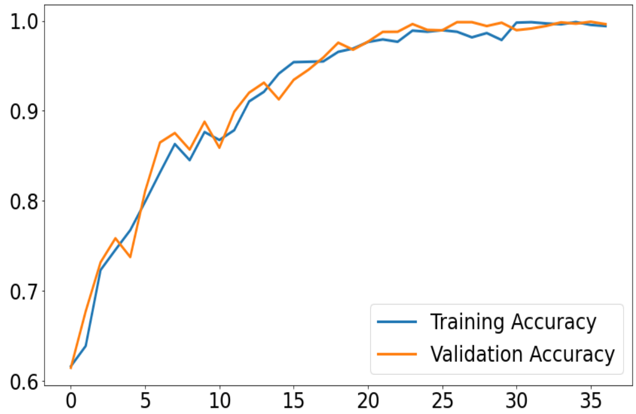
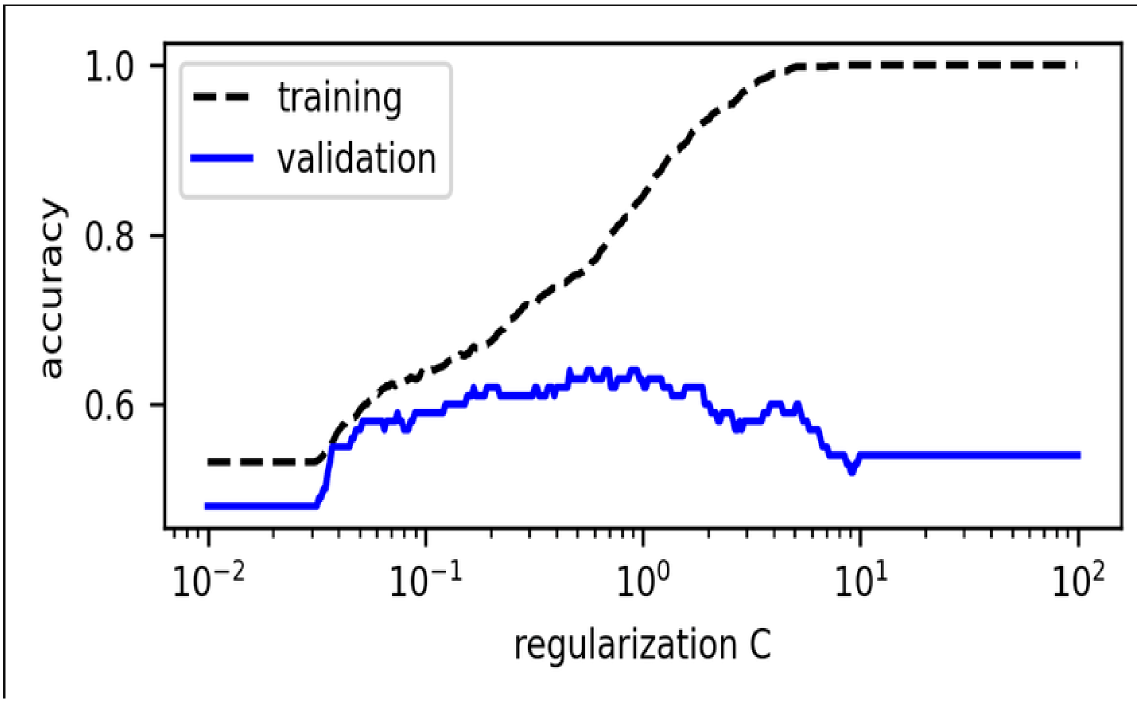


Epoch	Train_Acc	Train_Loss	Val_Acc	Val_Loss	Ensemble_Acc	Ensemble_Loss
1	81.096	1.135	92.551	0.402	84.903	0.418
2	92.468	0.388	95.028	0.285	94.307	0.160
3	96.039	0.254	96.954	0.206	97.048	0.085
4	97.229	0.197	97.238	0.193	98.036	0.059
5	97.995	0.162	97.491	0.163	98.507	0.043
6	98.529	0.133	97.364	0.163	98.825	0.035
7	98.716	0.120	98.074	0.133	99.457	0.018
8	98.847	0.112	98.074	0.129	99.649	0.011
9	99.145	0.096	97.459	0.146	99.730	0.009
10	99.635	0.078	98.532	0.106	99.755	0.008
11	99.813	0.068	98.453	0.107	99.760	0.008
12	99.866	0.065	98.848	0.098	99.877	0.005
13	99.955	0.060	98.832	0.098	99.900	0.004
16	99.978	0.057	98.769	0.096	-	-

Table 2. Full training procedure of both models with training and validation values

Fig # 13: C Regularization on Training Then Validation



Reflecting its innovative architecture and best performance, the graphical trends show that EfficientNet-B7 obtains the highest verification accuracy and lowest loss. ResNet also performs rather well, particularly in preserving constant validation measures over epochs. CNN exhibits good learning behaviour but needs adjustment to get more accuracy. The graph of SVM shows that its accuracy is somewhat sensitive to feature superior and parameter choosing. These images confirm that on challenging datasets, more advanced architectures such as Efficient Net generalise better. With 99.6% accuracy, the proposed Hybrid CNN + SVM method shows that integrating deep feature extraction with a strong classifier greatly increases diagnostic accuracy when compared to all else.

5. Discussion

This work proves the effectiveness of deep learning models for skin cancer classification, most notably the application of CNN and Transformer learning using models such as ResNet50 and Efficient Net. The Hybrid CNN + SVM model achieved the highest classification accuracy of 99.6% among all the tested models and thus the most viable for practical application. The Hybrid CNN + SVM model offers a new method of skin cancer classification by the integration of deep and machine learning. This work offers significant insights into the applicability of deep learning for skin cancer detection and provides a scalable and effective solution for automatic detection. The use of deep learning models such as CNN, SVM, ResNet-50, and Efficient-Net has greatly improved the accuracy and effectiveness of skin cancer detection and classification. These models are highly skilled at feature extraction and classification, with potential applications as early diagnostics. Issues with dataset bias, especially with regards to skin tones, and the requirement for large, diverse datasets remain, but they are key to building universally applicable diagnostics. The present research provides a solid foundation for future research to further develop stronger, interpretable, and balanced AI-based diagnostics for dermatology.

For future research, there is a need for the development of diverse and representative skin lesion datasets to reduce bias, particularly on skin tone and population variation. Multimodal incorporation of clinical history and genetic details has the potential to improve diagnostic accuracy. Explainable AI models should be developed for building trust and for clinical integration. Optimal deployment on mobile and edge devices in resource-limited settings is another area for improvement that raises wider accessibility. To guarantee that AI technologies are clinically relevant and successful, technologists and dermatologists must work together; this will eventually help to improve early diagnosis and patient upshots in skin cancer treatment For future research, there is a need for the development of diverse and representative skin lesion datasets to reduce bias, particularly on skin tone and population variation. Multimodal incorporation of clinical history and genetic details has the potential to improve diagnostic accuracy. Explainable AI models should be developed for building trust and for clinical integration. Optimal deployment on mobile and edge devices in resource-limited settings is another area for improvement that raises wider accessibility. To guarantee that AI technologies are clinically relevant and successful, technologists and dermatologists must work together; this will eventually help to improve early diagnosis and patient upshots in skin cancer treatment

6. Patents

This section is not mandatory but may be added if there are patents resulting from the work reported in this manuscript.

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Conflicts of Interest: Declare conflicts of interest or state "The authors declare no conflict of interest.

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