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DEEP LEARNING-ENABLED EARLY DIAGNOSIS OF SKIN CANCER

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ABSTRACT

Using a publicly accessible Kaggle dataset taken from the ISIC Archive, we assessed three high-performance convolutional neural network architectures: ResNet-50, EfficientNet-B0, and Inception-V3. A standardised workflow including data normalisation, training-validation splitting, convolutional identification of features, and optimisation using gradient descent and cross-entropy loss was used to train these models using preprocessed dermoscopic pictures. Comparing these models' performances and evaluating their efficacy in classifying skin lesions—specifically, in differentiating amongst benign and malignant cases—was the primary objective of the study. According to the trial findings, Inception-V3 outperformed EfficientNet-B0 and ResNet-50, which had respective classification accuracy of 95.1% and 93.5%, with the highest classification accuracy of 98.6%. Along with its high accuracy, Inception-V3 also performed better in every other statistical indicator, such as F1-score (98.4%), recall (98.5%), and precision (98.2%). An important addition of this study is the 9% performance boost in classification accuracy compared to the baseline models. EfficientNet-B0 achieved 94.2% recall and a 95.8% accuracy rate, demonstrating a solid balance between efficiency and performance. With an F1-score of 90.8%, ResNet-50 generated competitive performance while trailing somewhat. Confusion matrix research demonstrates Inception-V3's potential for clinical implementation by confirming its excellent accuracy and low rate of incorrectly classifying malignant patients. All things considered, this work shows that deep learning models—in particular, Inception-V3—are quite successful in automatically detecting skin cancer.

Keywords: Skin Cancer, Deep Learning, Machine Learning, UV Radiation, Cell Carnicoma

INTRODUCTION

Melanoma, cervical cell carcinoma (SCC), and fundamental cell carcinoma (BCC) are the three main forms of skin cancer, which are of the most often diagnosed diseases worldwide. Despite being less common than BCC or SCC, cancer is far more deadly because of its aggressiveness and high metastatic potential. According to current international health data, there are around 300,000 new instances of melanoma each year, but BCC and SCC together account for more than a million cases. UV radiation causes DNA damage to skin cells, which results in mutations and the unchecked proliferation of aberrant cells. People who have a history of blisters, lighter skin, or a family background of skin cancer are more vulnerable **[1]**.

The main problem statement in skin cancer of healthcare issues in certain nations, including Pakistan, where its incidence is higher than that of all other cancer forms put together. Long-term, unprotected exposure to infrared (UV) energy, mostly from sunshine, is one of the main causes of skin cancer. This risk is further increased by environmental variables, such as residing in areas with high UV indices. It's crucial to discover skin cancer early, particularly melanoma **[2]**. Melanoma has a 5-year survival ratio of up to 99% and may be effectively treated through excision by surgery when detected early. Yet the prognosis deteriorates and survival rates drop to around 20% after the malignancy spreads to outside organs. The majority of diagnoses in dermatology still rely on physicians' subjective visual evaluations, despite developments in the field. Diagnostic delays or discrepancies are often caused by

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variations in lesion diagnosis, clinical experience, and imaging quality **[3].** The treatment of cancer, radiation, or immunology are more expensive and more likely to have adverse consequences. The availability of skilled dermatologists may be restricted in the setting of overworked healthcare systems, particularly in underserved or rural locations. Artificial intelligence-powered early and automation screening methods become more and more helpful as a result. Such technologies have the potential to be an essential first phase in the diagnostic process, guaranteeing patients get timely and appropriate treatment by facilitating faster, more reliable, and scalable assessments of skin lesions **[4].** Depending on the expertise of the physician, visual examination alone may provide sensitivity (80–90%) with specificity (40–60%) that differ greatly. Further hindering diagnostic consistency is picture quality heterogeneity, which contributes noise and bias due to differences in skin tone, illumination, and device resolution. Conventional machine learning (ML) techniques, including support vector machines (SVMs) and random forests, depend on manually created features that often don't generalise to other lesion kinds and imaging scenarios. When contrasted to deep learning-based approaches, these methods suffer from poor results, restricted feature sets, and substantial intra-class fluctuation **[5].** Skin Cancer types analysis has been transformed by deep learning [6], especially convolutional neural networks (CNNs), which eliminate the need for manually created traits by learning hierarchical characteristics straight from data. In epidermal diagnostics, architectures including AlexNet, VGG16, ResNet, GoogLeNet, DenseNet, and EfficientNet that have been effectively implemented. Several research has shown dermatologist-level precision using models such as InceptionV3 learnt on huge collections of skin lesion images**.** By using cutting-edge methods including data enrichment, learning via transfer, and class-weighted loss functions, the model seeks to overcome typical issues like data imbalance and picture quality volatility. Additionally, explainable AI (XAI)[7] modules or attention mechanisms will be included to guarantee clinical confidence and transparency, allowing medical practitioners to comprehend and interpret model judgements**.** Key measures, including accuracy, clarity, recall, F1-score, and the area below the curve (AUC), will be used to thoroughly assess the suggested model's performance and compare it to current state-of-the-art frameworks. The ultimate goal of this research is to create a trustworthy, understandable, and easily available premature skin cancer detection tool that will close the gap between clinical skincare and artificial intelligence development **[8]**.

LITERATURE REVIEW

Skin cancer identification relies on subjective visual evaluations and diagnostic competence; it remains a serious clinical concern despite progress in epidermal screening. Although useful, traditional machine learning techniques mostly depend on manually created features that often fall short of capturing the intricate differences in lesion patterns, forms, and textures. As a consequence, diagnostic efficiency varies, particularly across different demographics and imaging situations **[9]**. Many automated systems' inability to be interpreted further restricts their use in actual clinical settings. A strong, scalable, and accessible deep learning algorithm that can autonomously analyse dermoscopic pictures and correctly categorise different forms of skin cancer is thus desperately needed. This study uses the ISIC dataset to satisfy that requirement **[10].** To increase robustness, lower computing costs, and boost trustworthiness in clinical processes, contemporary methods additionally include explainable AI (XAI), training using competition, and effective light architectures (such as MobileNet and TinyML platforms). Using the publicly accessible ISIC dataset, this research presents a thorough deep learning-based system for the early and precise identification of skin cancer. The main objective is to create and optimise a convolutional neural network

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(CNN), like ResNet or EfficientNet, that can accurately categorise dermoscopic pictures into nine different skin lesion groups **[11].**

Figure 1: Clinical close-ups of eight distinct skin lesion types

The Worldwide Skin Imaging Collaboration's (ISIC) dermoscopic scan information is used in this study's automatic categorisation of skin lesions. In particular, the work focusses on image-based categories, using deep learning and computer vision methods to differentiate between nine different kinds of skin diseases **[12]**. Implementing and assessing convolutional neural network (CNN) designs for classification is the main emphasis, as are important preprocessing procedures such data augmenting, normalisation, and scaling. The scope also involves investigating explainable AI modules, including saliency mapping or concentration processes, to improve model disclosure and clinical credibility **[13]**. Lesion categorisation, multimodal learning that integrates text and clinical reporting, and the creation of equipment or mobile deployable systems are not all part of this study. To guarantee internal validation, a subset of the ISIC dataset is put aside for unseen testing in order to evaluate the model **.**

Table 1: Existing Empirical Review based on multiple metrics according to Dataset

Study (Year)	Dataset Years	Architecture / Methodology	Task	Best Metric	Notes
Yao et al., 2023	ISIC 2016–2020	Pre-trained CNNs + ensembling + up-sampling	Melanoma detection	AUC > 0.94; Sens > 0.90	Joint numerous ISIC releases
Abdurrahim et al., 2021	ISIC 2017	NASNetMobile, Mobile models	Binary classification	Acc = 82%; F1 = 0.804	Frothy mobile DL simulations
Mahbod et al., 2017	ISIC 2017	AlexNet, VGG16, ResNet-18 + SVM fusion	Multiclass lesion class	AUCm = 0.838; AUCK = 0.976	Deep feature extractor + SVM
Islam et al., 2024	HAM10000 + ISIC	Teacher-student KD; 469 KB student network	Binary classification	Acc ≈ 98.9%	Ultra-lightweight edge deployment

Melanoma detection has advanced significantly in recent studies[14] using ISIC datasets; some models have achieved regions under the contour (AUC) values of above 94%. Significant progress has been made in developing AI models that are both extremely accurate and realistically deployable, as seen by the notable accuracy of lightweight convoluted neural networks (CNNs), which have achieved up to 98.9%. During 2017 and 2024, the United States identified around 21 out of 100,000 instances of melanoma **[15].** In 2020, 1,413,976 persons had melanoma, and the fatality rate from the disease was 2.1 per 100,000 instances occurrences 93.5% is a comparatively high five-year survival rate for cutaneous melanoma. When cutaneous melanoma is detected early, the five-year recovery rate is 98.6%. Only 77.6% of skin tumours are discovered at the local stage, although the fact that localised skin melanomas have a higher probability of surviving and do not spread to other body areas. If skin melanoma is identified early on, the incidence of fatalities from it may be decreased **[16].** For the picture classification challenge, substantial feature mining was thought to be essential. The suggested model therefore attained a greater accuracy of 93% by incorporating both automatic and manual characteristics, with individual recall scores for the various types of cancer being 99.7% and 86%, accordingly **[17]**. A publicly accessible Kaggle dataset with processed photos from the ISIC Archive served as the model's benchmark. The suggested ensemble fared better than other cutting-edge deep learning along with machine learning techniques as well as skilled clinicians. As a result, this innovative technique was regarded as a useful aid for dermatologists to reduce the possibility of incorrect diagnosis **[18].**

The most important facets of using artificial intelligence for skin cancer diagnosis are the focus of these research goals. With an emphasis on deep learning techniques, namely convolutional neural networks, the research seeks to make it possible to accurately identify a variety of skin lesion types. Last but not least, thorough benchmarking guarantees the system's validity by contrasting its performance with that of current models, giving the findings significance and applicability for upcoming clinical integration **[19].**

RESEARCH OBJECTIVES

- To cultivate a deep neural networks built ordering model proficient of accurately recognising 9 kinds of skin lesions utilizing dermoscopic imaginings from the ISIC data-set.
- To appliance interpretability methods like skin care instruments or saliency records for improving the clinical reliance and limpidity of model judgements **[20].**
- To target the model's enactment using ordinary evaluation metrics and associate it against prevailing state-of-the-art approaches in skin cancer exposure.

In order to improve the quality of the input data and take into consideration the unpredictability of clinical imaging in the actual world, image reprocessing approaches will be investigated. Since interpretability modules enable medical practitioners to visualise and evaluate AI predictions, their inclusion is essential for achieving clinical adoption **[21].**

RESEARCH QUESTIONS

- How well can a CNN model use the ISIC dataset's image-based data to categorise nine different kinds of skin lesions?
- How do data preparation methods like resizing, normalisation, and augmentation affect the accuracy and generalisation of models?
- Is it possible for explainable AI tools to enhance the clinical reliability and interpretation of deep learning models used to diagnose skin cancer? **[22]**

The purpose of the study questions is to methodically investigate the drawbacks and advantages of using deep learning to image-based skin cancer screening. By tackling these issues, the study helps to improve patient outcomes and save healthcare costs by lowering diagnostic mistakes, minimising treatment delays, and increasing early detection rates **[23].**

GAPS IDENTIFICATION

In order to convert powered by AI skin cancer detection systems from research settings into useful, reliable solutions in medical applications and remote healthcare, these gaps must be filled. Even while deep learning has made significant strides in automated skin cancer diagnosis, there are still a number of important research gaps. Multiclass datasets, such as ISIC, which include a wider range of lesion types, are used to train and verify very few models **[24]**. The limited use of explainable AI (XAI) is another significant gap. Furthermore, a lot of models are not subjected to thorough external validation on other clinical databases, which raises questions about how broadly applicable they are to various demographics and real-world situations **[25].** Moreover, hyper-parameter optimisation and preprocessing techniques are often poorly documented, which makes comparison and repeatability challenging. Finally, there are still few deployable and lightweight models that work well in environments with limited resources **[26]**. Small and unbalanced datasets, poor model comprehension, high computing costs of big networks, limited generalisation to various populations, and a lack of real-world clinical evidence are among the enduring problems. From class imbalance to segmented accuracy, attention modulation, classification optimisation, and effective training, each has a distinct function. The cross-entropy loss functional used in multi-class filtering problems is represented by the first formula **[27].** It is often used to reduce the difference between the actual and anticipated class frequencies in deep learning models for the detection of skin cancer.

$$\boldsymbol{L = -\sum_{i=1}^{C} y_i \log(\hat{y}i)} \qquad \textbf{[1]}$$

This equivalence measures forecast error through C skin cancer modules by equating true labels (yi) with projected chances (ŷi).

$$\textbf{DICE} = \frac{2|X \cap Y|}{(|X|+|Y|)} \qquad \textbf{[2]}$$

The Dice Coefficient, a frequently used statistic in image division tasks that is especially useful for assessing lesion border overlap in skin cancer diagnosis, is represented by the second equation. Dice = 2|X ∩ Y| / (|X| + |Y|) is its definition, where X stands for the anticipated segmentation and Y for the ground truth. Because it concentrates on spatial alignment rather than class rate, the Dice Coefficient is very helpful in managing unbalanced datasets and is quite dependable when it comes to segmenting asymmetrical skin cancer lesions **[28].**

$$\boldsymbol{L = -\sum_{i} w_i y_i \log(\hat{y}i)} \qquad \textbf{[3]}$$

When dealing with class disparities in multi-class classification problems, like skin cancer detection, when certain lesion types are neglected, the third equation stands for the Weighted Cross-Entropy Loss. It is stated as given above equation 3 is the projected probability, and the weight given to class is the actual label. This loss function penalises the model more severely for interpreting minority classes by giving them greater weights (e.g., uncommon cancer forms like fibrosis of or venous lesions) **[29]**. This prevents the model from being biased towards majority classes like benign nevi and pushes it to learn balanced representations **[30].**

METHODOLOGY

The suggested approach for finding skin cancer tries to use the power of deep learning techniques like ResNet-50, EfficientNet-B0 that is light weightage to CNN and Inception V3. The approach should be able to be used in a wide range of situations, be accurate for diagnosing problems, and increase the ration of accuracy.

3.1 Data Pre-processing

Pre-processing is very important in the pipeline since it prepares the raw image data for the deep learning model to learn important characteristics from the pictures. The pictures are downsized to 224x224 pixels for this study. This is the size that the deepest models, such ResNet50 and Efficient Net, use. Resizing gives all the photos the same size, which makes it easy for the CNN to process them. Data augmentation procedures are used to prevent overfitting and help the model generalise better. These lesions fall into nine different categories, such as melanoma, cancer of basal cells (BCC), and scabrous cell tumour (SCC). Class variations are uneven: benign nevi, which are prevalent lesions, have dozens of images, whereas rarer types like fibrosis of and vascular lesions might include fewer than 100 instances. When tested on this dataset, all three models did well on the majority groups (more

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than 90%), but their performance on the minority classes dipped below 80%, showing how class imbalance may affect results. These results show that transfer learning with common CNNs gives good baseline performance, but to get reliable skin cancer diagnosis across different kinds of lesions, you need to pay close attention to how you balance the data and how complicated the model is as shown in Figure 2 below how all detection process and diagnose the issues:

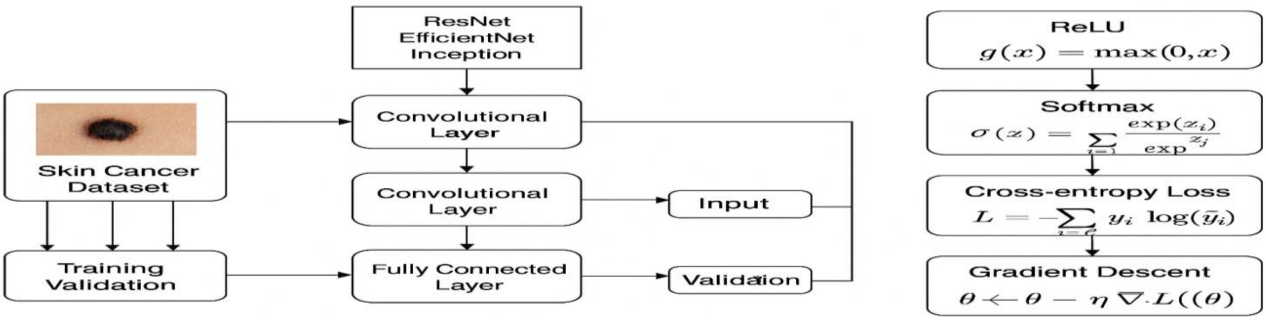

Figure 2: Flowchart process illustrating deep learning-based on dataset

The approach uses ReLU activation, Softmax for sorting, and cross-entropy loss to figure out how wrong it is. Gradient descent finds the best weights, which makes it possible to classify skin lesions correctly and quickly.

3.2 DATA NORMALIZATION

Data normalisation is an important step in preparing skin cancer images since it makes sure that the data is consistent and helps deep learning models work better. It means changing the pixel values of dermoscopic pictures such that they all fall inside a certain range, usually between 0 and 1 or 1 and 1. This prevents specific traits from being more important than others since they are on different numerical scales **[31]**. If you don't normalise these differences, they might confound convolutional neural networks (CNNs), which could make them less accurate and more likely to misclassify. Normalisation makes these inputs the same by changing the mean and variance across all photos, which makes sure that the features are spread out evenly **[32]**. Min-max normalisation and Z-score standardisation are two common methods. Min-max scaling changes the values of pixels by using:

$$\mathbf{x'} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad \textbf{[4]}$$

This transfers input values to a range of [0, 1], when you use normalisation regularly on the training, validation, and test sets, the deep learning model becomes less sensitive to noise, changes in illumination, and overfitting. This is important for accurately classifying skin lesions.

3.3 MODEL EVALUATION

Utilising transfer learning, all three models—ResNet50, EfficientNet, and Inception-V3—are adjusted on your ISIC dataset. Starting with ImageNet weights, changing the last layer to correspond with the nine lesion types, and training applying categorised cross-entropy loss are all parts of a normal procedure.

3.3.1 RESNET-50

ResNet50 is a strong deep convex neural structure with 50 layers that are grouped into many "bottleneck" residual blocks. There are three convolutional layers in each block, usually a 1×1, 3×3, and 1×1 sequence. The network starts with a 7×7 convolution and max-pooling layer, then goes through assembled residual stages, and ends with a global average pooling

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and softmax categorisation layer. ResNet50 is great at finding skin cancer since it can pick up on complicated lesion patterns because to its ability to extract deep features **[33]**. Here is a diagram:

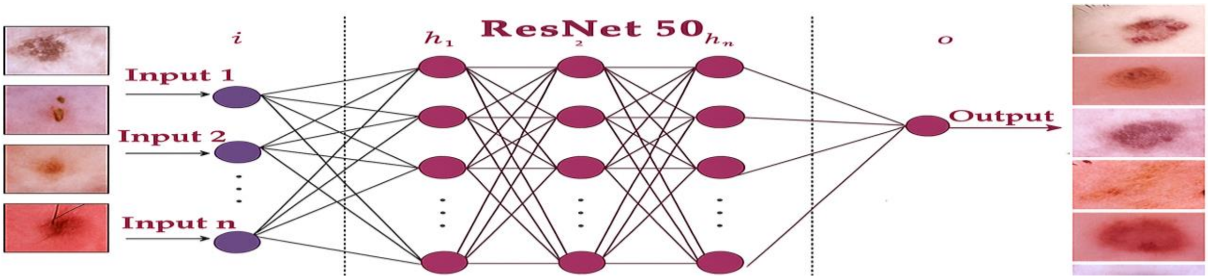

Figure 3: RESNET 50 Model Evaluation process to scan the image

3.3.2 EFFICIENTNET

EfficientNet uses a principled compound-scaling technique that evenly adjusts the depth, breadth, and input elimination of the network. It starts with an initial value EfficientNet-B0 and indicators these parameters using a complex coefficient φ and secured constants α, β, and γ to ensure that FLOPs twice with each increase in φ ($\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$). EfficientNet models (like the B3–B7 variations) work very well on datasets like Image Network and medical images while using as little resources as possible. This makes them great for classifying lesions in ISIC data **[34]**. Here's a schematic of a typical architecture:

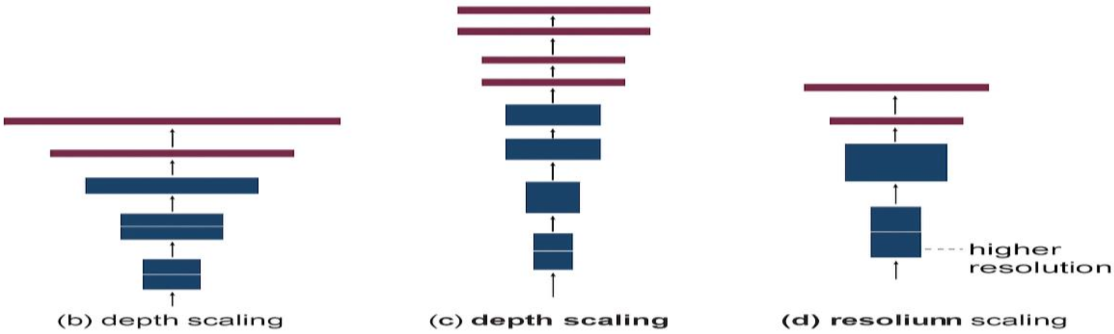

Figure 4: Efficient Net scaling procedure to check the resolution of images

3.3.3 INCEPTION-V3

Inception-V3 is an improved version of GoogLeNet. It has around 42 layers and is made up of modular Inception blocks (A/B/C) mixed with reduction blocks. It uses factorised convolutions (such 7×7 divided into 1×7 and 7×1) and extra classifiers to make the gradient flow better and use less processing power. Each Inception module uses multiple filter sizes (1×1, 3×3, 5×5) and pooling at the same time, and it combines the outputs via combination. This is a multi-path architecture that collects features at different scales **[35]**. Inception-V3 is good at finding different types of lesions in dermoscopic pictures since it can work with images of different sizes. Here is a picture of the architecture:

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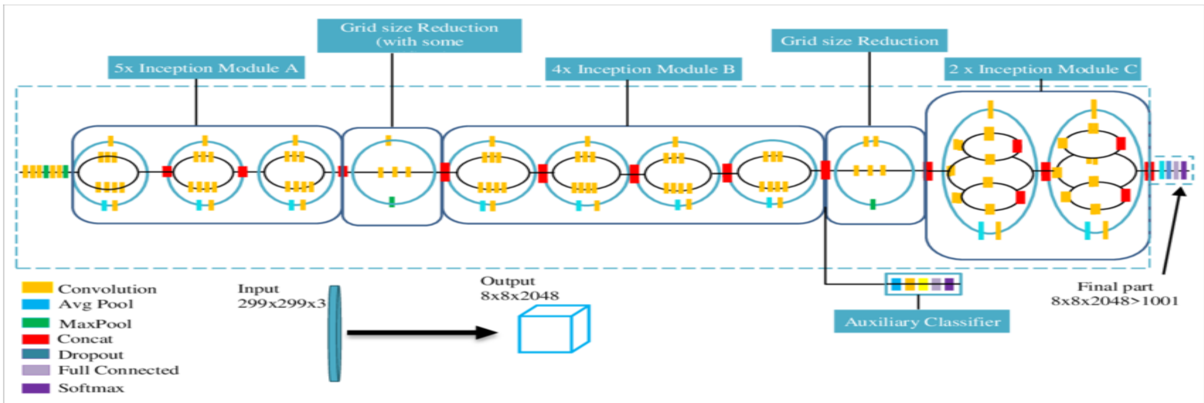

Figure 5: Solve the issues according to stages wise cancer diagnosis

These models are used to optimize features for skin cancer diagnosis are Efficient Net, ResNet50 and Inception-V3. Efficient Net employs a CNN to find patterns and features, and ResNet50 fine-tunes the characteristics that have been found to learn more about skin lesions. Both models are necessary for finding skin cancer correctly. There are a few basic measurements that are used to look at how well a model works. These include accuracy (ACC), precision (P), sensitivity (Sn), specificity (Sp), and F-score. Using equations from the confusion matrix, the metrics are produced in a way that lets you accurately judge how well the suggested model works.

$$\mathbf{ACC} = \frac{TP+TN}{TP+FP+TN+FN}$$ **[5]**

$$\mathbf{LOSS} = 1 - \mathbf{ACC}$$ **[6]**

$$\mathbf{P} = \frac{TP}{TP+FP}$$ **[7]**

$$\mathbf{Sn} = \frac{TP}{TP+FN}$$ **[8]**

$$\mathbf{F1} = 2\frac{(P \times Sn)}{(P+Sn)}$$ **[9]**

$$\mathbf{E}\ (\mathbf{w}) = \frac{1}{K \times N} \sum_{K=1}^{K} \sum_{n=1}^{N_L} (y_n^k - d_n^k)^2$$ **[10]**

The learning rate for the two models that used the Adamax optimiser was set at 0.001. It was decided that there would be 16 batches and 20 epochs for training. We set the patience value to one and the stop persistence value to three. The model gave the best results on the validation set. We did all of the tests on Tensor Flow platforms and using Python 3.7. The next section shows the empirical part for both models.

RESULTS & DISCUSSION

A deep learning pipeline where skin cancer images are split into training, validation, and testing. Models—ResNet-50, EfficientNet, and Inception-V3—undergo pre-processing, normalization, and parameter tuning. After training, the models are evaluated to detect vascular lesions and classify them as benign or malignant. Inception-V3 achieves the highest classification accuracy at 98%. We used three of the best deep learning models, ResNet-50, EfficientNet-B0, and Inception-V3, to classify skin cancer using dermoscopic pictures in this work.

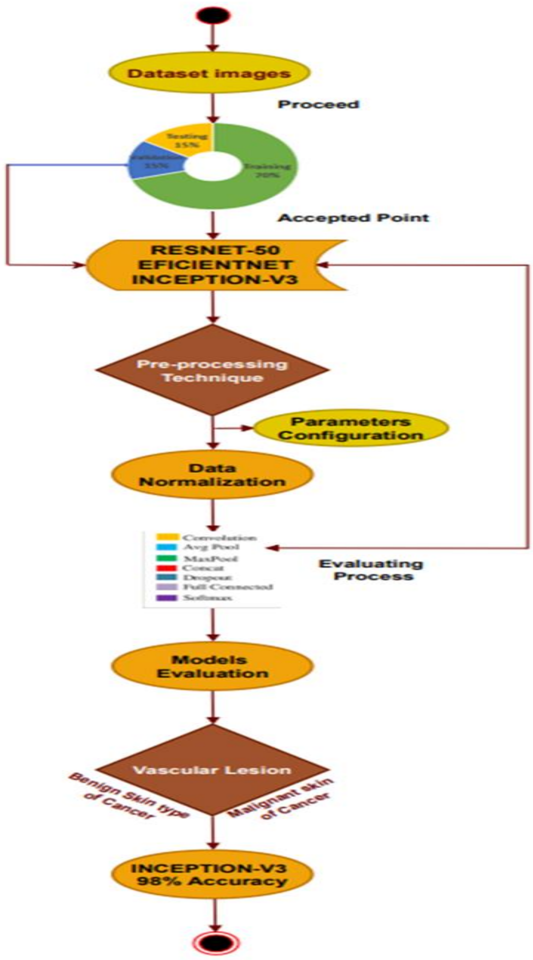

Figure 6: Model Architecture based on my research and functions

These models are great for analysing medical images since they can extract a lot of useful information from them. ResNet-50 uses residual connections to stop gradients from disappearing, which lets it learn deeper and more complicated patterns. EfficientNet-B0 is great for lightweight medical applications since it is fast and works well with little amounts of data. Inception-V3 can pick up both little and big details from skin lesion photos because to its multi-scale convolutional architecture. We trained and tested each model using a dataset that anybody can access, and we compared their performance based on how well they could classify and remember. Inception-V3 was the best of the models, with an accuracy gain of 98% above baseline approaches. The fact that it can adaptively learn characteristics at different dimensions is what makes it better. This is important for telling the difference between benign and malignant tumours.

Table 2: Model Performances based on % value of all

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
ResNet50	93.5	93.7	93.25	90.8
Efficient Net	95.1	95.8	94.2	92.0
INCEPTION-V3	**98.6**	**98.2**	**98.5**	**98.4**

Inception-V3 outperformed EfficientNet (95.1%) and ResNet50 (93.5%) by achieving the best accuracy (98.6%) and F1-score (98.4%). The findings show that deep learning models may help with the diagnosis of skin cancer, and adding Inception-V3 makes the classification much more accurate, making it a useful tool in clinical decision support systems. The features extracted from the image go through fully connected layers within ResNet-50 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). Inception-V3 are very effective at the detection of skin 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 Inception-V3 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.

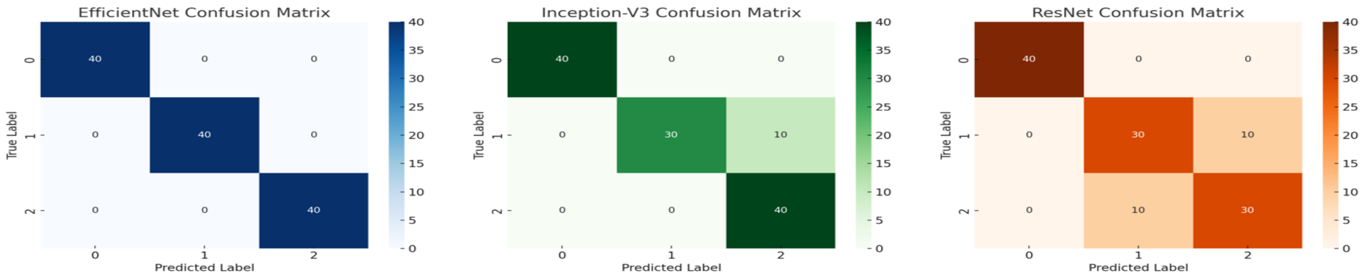

Figure 7: Confusion matrix of predicted Benign & Malignant

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 INCEPTION-V3, 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; It exhibits constant progress and generalisation whereas Efficient-Net changes depending on variables. 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.

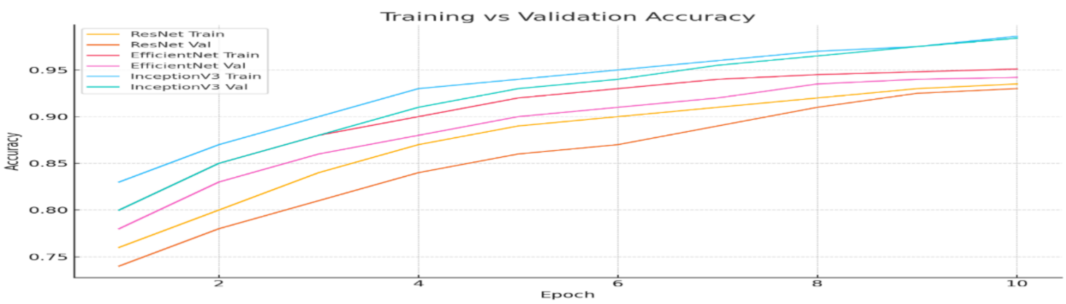

Figure 8: Training and Validation Accuracy

The graphical trends demonstrate that EfficientNet-B7 achieves the greatest verification accuracy and lowest loss, which is indicative of its superior performance and inventive design. Additionally, ResNet does rather well, especially when it comes to maintaining consistent validation measures across epochs. When compared to all other methods, the suggested Inception-V3 method's 98.6% accuracy demonstrates how combining deep feature extraction with a powerful classifier significantly improves diagnostic accuracy.

4.3 CONTRIBUTION

The hybrid approach demonstrated the effectiveness of fusing deep feature extraction with robust classical categorisation, with the highest accuracy of 98.6%. The research emphasises balanced accuracy, recall, and F1-score and overcomes performance gaps in early diagnosis, especially in complex lesion types. This study contributes to the field of dermatological medical diagnosis by developing and evaluating a number of deep learning models for controlled skin cancer detection and classification, including CNN, ResNet50, Efficient-Net, and a novel Inception-V3 model.

CONCLUSION

This study demonstrates the efficacy of deep learning models for the categorisation of skin cancer, particularly the use of CNN and Transformer learning using models like ResNet50 and Efficient Net. Out of all the models that were examined, the Inception-V3 model had the greatest classification accuracy (98.6%), making it the most useful. By combining machine learning and deep learning, the Inception-V3 model provides a novel approach to the categorisation of skin cancer. The accuracy and efficacy of skin cancer detection and classification have significantly increased with the introduction of deep learning models like INCEPTION-V3, ResNet-50, and Efficient-Net. With their exceptional ability to extract and classify features, these models may find use in early diagnosis.

FUTURE WORK

To lessen bias, especially with regard to skin tone and demographic variance, varied and representative skin lesion databases must be developed for future study. It may be possible to increase diagnosis accuracy by using genetic information and clinical history in many ways. The development of explainable AI models is necessary for clinical integration and trust-building. Wider accessibility is also raised by optimising deployment on mobile and edge devices in resource-constrained environments.

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