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# A FUSED PARALLEL RESNET MODEL FOR ENHANCED SKIN CANCER DETECTION

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**Abstract**

To achieve high survivability quotient, there is the need to have precise diagnostic procedures that will help in early cancerous skin detection as it remains one of the problems of life taken by cancer all over the world. The visual jobs by dermatologists in clinical diagnosis are found to be subjective and time consuming in examinations. This paper propose a deep learning model based on dual-branch ResNet50 and ResNet100 to help handle the problem of poor performance in both feature extraction and classification. In TensorFlow, the ImageDataGenerator component serves the purpose of preparing data, as well as its improvement prior to the distribution of the dataset into training and validation. The feature representations of the two ResNet networks are pretrained through ImageNet prior to concatenation of the vectors so that they can be processed through full-connected layers and other groups such as batch normalization and global average pooling of the information until they are subjected to encoding through softmax multi-class classification. Checkpointing of the system can allow the continuity of training and system resilience. ResNet50-ResNet101 exhibited the high predictive consistency by lowering biases along with the increased robustness to data variations that results in the higher accuracy of detection across multiple types of lesions. The quality of the method is measured in terms of Accuracy, Brier Score and Cross-Validation Score as well as Grad-CAM and LIME (Local Interpretable Model-agnostic Explanations) to make it reachable. The detection system demonstrated a high potential in skin cancer detection due to the accuracy of classification to 95%.

**Keywords:** Deep Learning, Transfer Learning, ResNet50, ResNet101, Skin Cancer Classification, Medical Image Analysis, TensorFlow, Data Augmentation, Model Checkpointing, Hybrid CNN, Feature Extraction

## 1. Introduction:

One of the most widely spreading diseases in the world is skin cancer, and survival rates are greatly increased by early identification. While visual inspection and biopsy are still the mainstays of traditional diagnostic techniques, advances in deep learning and artificial intelligence have made it possible to diagnose skin cancer through medical imaging in a way that is automated, accurate, and efficient. With the help of transfer learning for effective feature extraction, this suggested study uses a dual-branch architecture based on ResNet50 and ResNet101 to create a deep learning model for image categorization. It employs a state-saving

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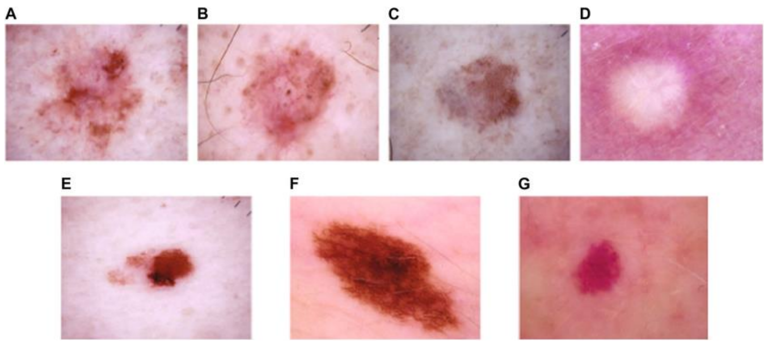
method to resume training from the most recent stored epoch in the event of disruptions, and it integrates data augmentation with ImageDataGenerator to improve generalization. To ensure robust feature representation, the collected features from both ResNet models are combined and run through thick layers prior to classification. To avoid data loss, the model is also stored on a regular basis (saved_model.keras). This method is perfect for practical applications in skin cancer classification and detection since it is efficient and scalable, and it works well with huge image datasets. Long exposure to ultraviolet (UV) radiation from the sun, such as tanning beds, is the main cause of it. Skin cancer is one of the worst malignancies due to its high death rate. High ultraviolet (UV) radiation exposure causes the skin's melanocyte cells to proliferate rapidly, which has an impact on the healthy tissues [1]. It starts when the aberrant cells proliferate throughout the lymph nodes and obliterate the surrounding tissues [2]. This illness is a serious public health concern since it affects a sizable section of the American population. On average, five million cases of skin cancer are detected in the US each year [3]. Nearly one-third of all cancer-related deaths are caused by skin cancer, according to the World Health Organization. Similarly, there has been a significant rise in skin cancer cases in recent years[4].




(A) AKIEC, (B) BCC, (C) BKL, (D) DF, (E) MEL, (F) NV, and (G) VASC

Fig.1 Sample Images of each class in HAM10000 DATASET

## 2. Existing Work

Pradhumn Agrahari et al [5] proposed an effective multiclass skin cancer detection system having high-performance comparable to that of a dermatology expert. Pre-trained MobileNet model is employed for model building. For training HAM10000 ISIC dataset is used. The model detects skin lesion with a categorical accuracy as high as 80.81%, top-2 accuracy of 91.25% and top-3 accuracy of 96.26%. This is fast and expansible method that can hold the ability for impeccable clinical advancement, including widening the scope and scale of primary healthcare practice. Since the 1990s, there has been a significant rise in skin cancer incidence, and the annual death rate from the disease has nearly doubled. Ghadah Alwakid et al [6] proposed Deep Learning as a method for extracting a lesion zone with precision. First, the image is enhanced using Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) to improve the image's quality. Then, segmentation is used to segment Regions of Interest (ROI) from the full image. We employed data augmentation to rectify the data disparity.

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The image is then analyzed with a convolutional neural network (CNN) and a modified version of Resnet-50 to classify skin lesions. This analysis utilized an unequal sample of seven kinds of skin cancer from the HAM10000 dataset. With an accuracy of 0.86, a precision of 0.84, a recall of 0.86, and an F-score of 0.86, the proposed CNN-based Model outperformed the earlier study's results by a significant margin. The study culminates with an improved automated method for diagnosing skin cancer that benefits medical professionals and patients. Aarushi Shah et al [7] The study found that ANN and CNN were successful in early detection of skin cancer using different data sets and hybrid models, demonstrating the potential for these technologies to improve accuracy in skin cancer detection. The paper highlights the novelty of using deep learning techniques for skin cancer detection and emphasises the critical need for an automated system for skin lesion recognition to reduce effort and time in the diagnosis process. The possible applications of this study include the development of more efficient and accurate skin cancer detection systems that can lead to earlier diagnosis and improved treatment outcomes.

Overall, this research underscores the importance of using advanced technologies, such as ANN and CNN, in the fight against skin cancer and highlights the potential impact of these techniques in improving patient outcomes. G. Reshma1 et al [8] The presented model's performance takes place against the International Skin Imaging Collaboration (ISIC) dataset, and the experimental outcomes are inspected in different evaluation measures. The resultant experimental values ensure that the proposed IMLT-DL model outperforms the existing methods by achieving higher accuracy of 0.992. Mampitiya1et al [9] investigates the performance of classifying skin cancer dataset HAM10000 using ResNet50, MobileNet, and the traditional support vector machine (SVM) model. The dataset combines seven cancer types: actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, melanocytic nevus, and vascular lesion. The SVM classifier is designed to employ a histogram of oriented gradient (HOG) features with principle component analysis (PCA). Alzubaidi et al. [10] proposed a new approach for transferring learning to train an extensive ISIC dataset and transfer knowledge to a target dermatology dataset. Furthermore, CNNs, in which recent developments are combined, were used to diagnose skin lesions with high accuracy. Ajay et al [11] investigates the performance of various convolutional neural network (CNN) models like AlexNet, GoogleNet, VGGnet11, VGGnet13, VGGnet16, VGGnet19, ResNet18, ResNet34, ResNet50, ResNet101, ResNet152, DenseNet121, DenseNet161, DenseNet169, and DenseNet201 for brain tumor diagnosis tasks. Yong Wang et al [12] proposed an automatic architecture design method based on monarch butterfly optimization (MBO). Specifically, an expressive Neural Function Unit (NFU) based architecture representation is designed, which integrates promising architectures in GoogLeNet, ResNet and DenseNet to facilitate the joint search of macro-architecture and depth of CNNs. Furthermore, a direct architecture encoding is designed to take advantage of the fast convergent MBO, which exploits evolutionary operators that have no complex computations to continuously improve the architecture population via encoding optimization. Extensive experiments conducted on eight benchmark image datasets demonstrate that our method can achieve continuously competitive performance with much less time and computational overhead. Vatsala Anand et al [13] proposed a model has been validated by considering several useful hyper parameters such as different batch sizes of 8, 16, 32, 64, and 128; different epochs and optimizers.The proposed model is working best with an overall accuracy of 89.09% on 128 batch size with the Adam optimizer and 10 epochs and outperforms state-of-the-art techniques. This model will help dermatologists in the early diagnosis of skin cancers. Farida Siddiqi Prity et al [14] proposed a method which aims to introduce a novel multi-architecture hybrid deep learning model called "RvXmBlendNet," which combines the strengths of four individual models: ResNet50 (R), VGG19 (v), Xception (X), and MobileNet (m), followed by "BlendNet" to signify their fusion into a unified architecture. The integration of these models is achieved through a synergistic combination of architectures, incorporating self-attention mechanisms using attention layers and adaptive content blocks. This study used the HAM10000 dataset to refine dermoscopic image preprocessing and enhance deep learning model accuracy. Techniques like OpenCV-based hair removal, min–max scaling, and adaptive histogram equalization were employed to improve image quality and feature extraction. A comparative study between the proposed hybrid "RvXmBlendNet" and individual models (CNN, ResNet50, VGG19, Xception, and MobileNet) demonstrated that "RvXmBlendNet" achieved the highest accuracy of 98.26%, surpassing other models. a novel multiarchitecture hybrid deep learning model. This innovative model integrates the unique capabilities of four individual architectures: ResNet50, VGG19, Xception, and MobileNet, collectively termed "BlendNet" to signify their fusion into a unified architecture This integration is not merely a combination of well-known models but strategically leverages their complementary strengths to enhance performance beyond what each model achieves individually. Ahmad Naeem et.al [15] a deep learning model combining Xception and ResNet101 networks. The framework effectively classifies multiple skin cancer types, including melanoma and basal cell carcinoma. Utilizing datasets like PH2, DermPK, and HAM10000, the model achieved a prediction accuracy of 98.21%, demonstrating its potential in aiding timely skin cancer diagnosis. Alavikunhu Panthakkan et al [16] proposed concatenated X-R50 model is cutting-edge, with a 97.8% prediction accuracy. The performance of the model is also validated by a statistical hypothesis test using analysis of variance (ANOVA). The reported approach is both accurate and efficient and can help dermatologists and clinicians detect skin cancer at an early stage of the clinical process.

## 3 Methodology

The architectural diagram Fig.2 illustrates the complete workflow of a deep convolutional neural network model, specifically a residual network (ResNet) architecture, designed for image classification tasks. An input image is first pre-processed using zero-padding, then a convolutional layer, batch normalization, ReLU activation, and max pooling are applied. Following that, the network is divided into several phases, each of which consists of identity and convolutional blocks that aid in feature extraction while maintaining data via residual connections. These steps allow the model to acquire intricate hierarchical features by gradually deepening the network with larger filter dimensions. The last convolutional stage is followed by the flattening of the feature map and the application of average pooling to minimize dimensionality. The classification result is then obtained by passing the network output through a fully connected layer that has a softmax activation function. By using deep residual learning

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to address vanishing gradient problems, this modular and layered framework enables effective training and precise image recognition.

### 3.1. ResNet50

A notable deep convolutional neural network design for computer vision and image classification applications is the Residual Network-50. ResNet50, created by Microsoft Research, is a member of the ResNet (Residual Network) family, which popularized residual learning as a way to make training extremely deep networks easier. Convolutional layers, batch normalization, ReLU activation, pooling layers, and fully linked layers are among the 50 layers that make up ResNet50. Its primary innovation is the use of residual connections, which enable a layer's input to be directly appended to a deeper layer's output. This lessens the vanishing gradient issue that frequently arises in deep networks and aids the model in learning identity mappings. Because of this, ResNet50 may be trained effectively even at deeper levels, providing better generalization and accuracy than conventional CNNs. The architecture is structured into multiple stages, each containing a combination of convolutional blocks (which use projection shortcuts to match dimensions) and identity blocks (which preserve input dimensions). In many realistic deep learning applications, ResNet50 is a preferred option due to its harmony of depth, accuracy, and computational economy.

Convolution and identity blocks are used in stages two through five of the design. Learnable filters are applied within the convolutional blocks, however gradient flow is allowed to travel across shortcut connections. To finish the process, the framework uses a flattening layer and average pooling (average pool). Prior to the final layer converting feature maps into one-dimensional vectors, the average pooling functionality aids in reducing dimensions.

The final fully connected layer, which completes the classification process, produces the output predictions. ResNet-50's methodical architecture allows for both operational efficiency and performance in structuring hierarchical models[17].

### 3.2. ResNet101

Microsoft Research created the Residual Network-101, a deep convolutional neural network that is a member of the ResNet family. ResNet101 is deeper and more potent than its predecessor, ResNet50, because it has 101 layers, as its name impliesIt makes use of residual learning, a fundamental idea that tackles the degradation issue in deep networks, where the addition of more layers may result in increased training error. The bypass connection, often known as the shortcut connection, is the main innovation in ResNet101 and other ResNet variations. By eliminating one or more layers, these connections enable a layer's input to be added to the output, creating a residual block. By retaining gradient flow during backpropagation, this aids the network in learning identity mappings more effectively and makes it easier to train very deep architecturesThe architecture of ResNet101 is similar to that of ResNet50, but at some stages—especially in the middle layers—there are more residual blocks piled. Four important stages (Conv2_x to Conv5_x) with multiple convolutional and identity blocks each come after the initial convolution and max pooling layer. ResNet101 is well-suited for applications requiring high accuracy and nuanced feature recognition because

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of its enhanced depth, which enables it to capture finer details and complex elements in the input. Because of the effective residual block architecture, ResNet101 is still computationally manageable despite its depthIt is frequently employed as a backbone model in more intricate deep learning frameworks like Faster R-CNN or Mask R-CNN, and it is widely utilized in image classification, object recognition, semantic segmentation, and medical imagingPretrained weights for ResNet101 (trained on ImageNet), like those for other ResNet models, are frequently employed in transfer learning scenarios, where the model is adjusted for novel, domain-specific tasks using smaller datasets. Because of this, ResNet101 is an effective and adaptable solution for contemporary deep learning applications.

### 3.3. Proposed Method

A dual-branch convolutional neural network exists as part of the proposed approach for skin cancer classification by effectively uniting ResNet50 and ResNet101 framework strengths. The network architecture aims to enhance both the extraction of relevant features and classification precision and expanded operational ability across various skin lesions. Before model processing begins the system uses resizing together with normalization and augmentation methods such as rotation flipping and zooming to strengthen the model's capability to generalize. A pair of deep convolutional networks named ResNet50 and ResNet101 receives augmented images from the initial analysis step which were pretrained on the ImageNet dataset. By using pretrained models for transfer learning, users can minimize training time and prevent overfitting while utilizing hierarchical features during model training. Every component of the network feeds its inputs independently to extract multiple feature representations using convolutional stages with identity mapping blocks. The shallower configuration of ResNet50 enables it to identify mid-level and basic features whereas ResNet101 extracts high-level abstract semantic characteristics with its deep framework. Integration of batch normalization together with ReLU functions and strided convolution or max pooling forms part of stable training procedures that improve feature extraction in each convolutional layer sequence. Before final average pooling occurs in both ResNet branches (Conv5x) their feature maps undergo reduction to fixed-length vectors with retention of vital spatial characteristics. The feature vectors obtained from both ResNet50 and ResNet101 networks become merged into a consolidated feature representation. The feature integration process enables deep network learning to merge complementary features obtained from the shallow and deep components thus creating advanced classification features.

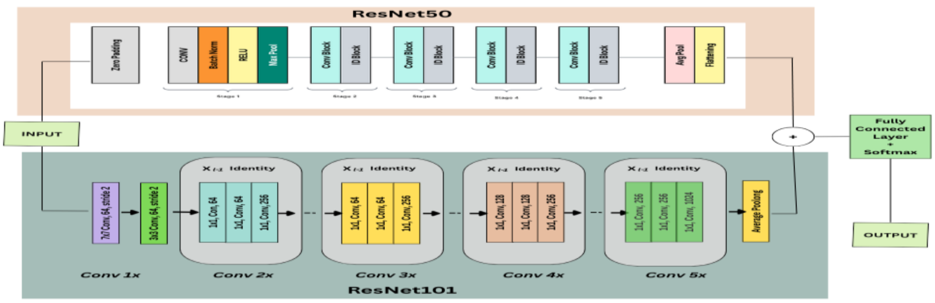


Fig 2. Flow of the Proposed model

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This combined vector gets transmitted through dense layers that contain normalization and dropout layers for preventing overfitting and achieving regularization. To facilitate precise classification, an output layer activation function creates probability distributions for target classes using softmax. The model saves its weights through checkpointing at regular intervals as a maintenance method for stability and interruption recovery. Grad-CAM with LIME (Local Interpretable Model-agnostic Explanations) serves as explainability techniques for interpreting model decision processes so healthcare providers can establish trust in vital clinical settings. Through merging the combined strengths of different architectures the dual-branch approach reaches a final classification accuracy of 95%. The combination of features in this design creates improved capability for fusion while allowing enhanced data resistance and generalization on different skin lesions which makes it an effective tool for early and precise skin cancer recognition.

**Algorithm: Dual-Backbone CNN Model using ResNet50 and ResNet101**

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**Input:** HAM10000

**Output:** Predicted class labels using Softmax layer
**Dataset Split:** 80% for training, 20% for validation

------------------------------------------------------------------------------------------------------

***Dataset preparation***

- Apply ImageDataGenerator for data augmentation and normalization.
- Convert image labels to numeric using LabelEncoder.

Feature Extraction

- Input image size: 224×224×3.
- Extract features using ResNet50
- Extract features using ResNet101

Features Fusion

Concatenate feature vectors obtained from both ResNet50 and ResNet101 backbones.

Classification Layer

- Pass the concatenated feature vector through a Fully Connected Dense Layer.
- Apply Softmax activation to predict the probability distribution across target classes.

The Dual-Backbone CNN Model utilizing both ResNet50 and ResNet101 begins with preprocessing the HAM10000 dataset by applying data augmentation and normalization using ImageDataGenerator, and converting categorical labels to numerical format via LabelEncoder. Each image is resized to 224×224×3 to ensure compatibility with both backbone models. The model then performs feature extraction in parallel using two powerful convolutional neural

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networks—ResNet50 and ResNet101—each of which captures rich hierarchical features from the same input image. Global Average Pooling is used to convert the output of each network into compact feature vectors. These vectors, representing different levels of abstraction, are then concatenated to form a unified, comprehensive feature representation. This fused vector is passed through a fully connected dense layer where a Softmax activation function computes the probability distribution across all target classes, ultimately producing the final predicted label for each image. This dual-architecture approach enhances classification accuracy by leveraging the complementary strengths of both networks.

## 4. Result and Discussion

The HAM10000 (Human Against Machine with 10,000 training images) dataset is a widely used benchmark dataset in the field of medical image analysis, specifically for skin lesion classification and melanoma detection. In all, the dataset contains 10,015 high-quality RGB dermatoscopic photos, all adjusted to 600 by 450 pixels. All images are from different types of pigmented skin lesions gathered from a variety of sources to maintain a diverse mix of patients and imaging situations. The diagnostic categories are actinic keratoses and intraepithelial carcinoma (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and vascular lesions (vasc). Even so, the classes exist in the dataset in very unequal proportions. Among all the images, the most are from the nv (melanocytic nevi) class at 6,705, with mel (2,113), bkl (1,099), bcc (514), akiec (327), vasc (142) and df (115). The problem of too many data examples in one class makes it hard for models to be unbiased, so it's necessary to apply techniques that help balance the data. Knowing these properties is vital for designing models that can be used in practice for dermatology.

The proposed model adopts a Dual-Backbone CNN architecture that leverages the combined strengths of two powerful deep learning models—ResNet50 and ResNet101—for the classification of skin lesions using the HAM10000 dataset. Initially, the dataset undergoes preprocessing, where image augmentation and normalization are performed using ImageDataGenerator to enhance model generalization. The class labels are converted into numerical values using LabelEncoder. All input images are resized to 224×224×3 to match the expected input dimensions of the backbone networks. Feature extraction is conducted in parallel using both ResNet50 and ResNet101, each extracting unique and complementary deep features from the input images. These features are then passed through Global Average Pooling layers to generate compact and meaningful representations. The resulting vectors from both models are concatenated to form a unified feature representation, effectively capturing a broader spectrum of image characteristics. This merged feature vector is fed into a fully connected dense layer, and a Softmax activation function is applied to output class probabilities. The model then predicts the most likely class for each input image, demonstrating improved performance through the fusion of multi-level deep features.

A noteworthy aspect of the proposed approach can run without using dedicated GPUs, giving access to researchers or practitioners who do not have strong computer systems. Training and evaluation were done on a standard computer with 8.00 GB RAM and Windows 11 OS. Even

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though this system proves the model works on normal hardware, training takes more time than other techniques. For instance, the latency of the model can go up to 72 hours while it processes a dataset like HAM10000. While it takes time, the model's robustness and practicality are clear because high-end hardware is not needed to use such a big dataset. This sacrifice of fast performance for better accessibility provides a strong reason why low-resource communities can use it more widely.

### 4.1. Performance Metrics

The amount of accurate forecasting the model made out of all the samples is known as accuracy. By dividing the number of accurate predictions by the total number of samples evaluated, it displays the model's overall correctness[18].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

The weighted Brier score as $\ell w$ with $w(c) > 0$ standardized to be a probability density function (PDF) with support over (0,1), which reflects a priori knowledge about the benefit-cost ratio in a particular clinical application of risk prediction model[19].

$$E[BS_w] \coloneqq E[\ell_w] = \int_0^1 L(c), w(c), dc, \tag{2}$$

Cross-validation is a statistical technique used to assess the predictive performance of a model by partitioning the data into subsets, training the model on some subsets, and validating it on the remaining ones. The general formula for calculating the cross-validation error, particularly in K-fold cross-validation, is

$$\mathrm{CV}(\hat{f}) = \frac{1}{N}\sum_{i=1}^{N} L\left(y_i, \widehat{f^{-\kappa(i)}}(x_i)\right) \tag{3}$$

Gradient-weighted Class Activation Mapping (Grad-CAM) is a widely used technique in deep learning for generating visual explanations of convolutional neural network (CNN) decisions. It highlights the regions in input images that are most influential for a model's predictions, enhancing interpretability

$$L^{c}_{\text{Grad-CAM}} = {}^{\text{ReLU}}\left(\sum_k \alpha^c_k A^k\right) \tag{4}$$

LIME (Local Interpretable Model-agnostic Explanations) s an algorithm designed to provide interpretable explanations for the predictions of any black-box machine learning model, particularly useful in image, text, and tabular data domains.

$$\underset{g\epsilon G}{arg\,min}\, L(f, g, \pi x) + \Omega(g) \tag{5}$$

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| S. No | Model | Accuracy | Brier score | Cross Validation score | | Grad-CAM | LIME (Local Interpretable Model-agnostic Explanations) |
|---|---|---|---|---|---|---|---|
| 1 | **EfficientNetV2-Small** | 0.853 | 0.843 | 0.755 | | 0.865 | 0.724 |
| 2 | **MobileNetV2** | 0.899 | 0.690 | 0.742 | | 0.558 | 0.528 |
| 3 | **DenseNet121** | 0.860 | 0.814 | 0.528 | | 0.498 | 0.787 |
| 4 | **AlexNet** | 0.854 | 0.597 | 0.653 | | 0.565 | 0.741 |
| 5 | **Proposed** | 0.958 | 0.798 | 0.663 | | 0.812 | 0.909 |

TABLE 1. COMPARISON OF FIVE DEEP LEARNING MODELS

Table 1 displays five deep learning models including EfficientNetV2-Small and MobileNetV2 and DenseNet121 and AlexNet and the Proposed hybrid model with an evaluation based on essential performance elements for skin cancer classification. The evaluation metrics consist of statistical measurements like classification accuracy, Brier score for calibration analysis and Cross Validation score for data split consistency next to interpretability tools Grad-CAM and LIME. The Proposed model stands out among all models in terms of both predictive success and explanation capabilities. The Proposed model demonstrates excellent performance consistency across all metrics which makes it an ideal solution for edical diagnosis because accuracy and transparency are primary considerations in such sensitive applications.

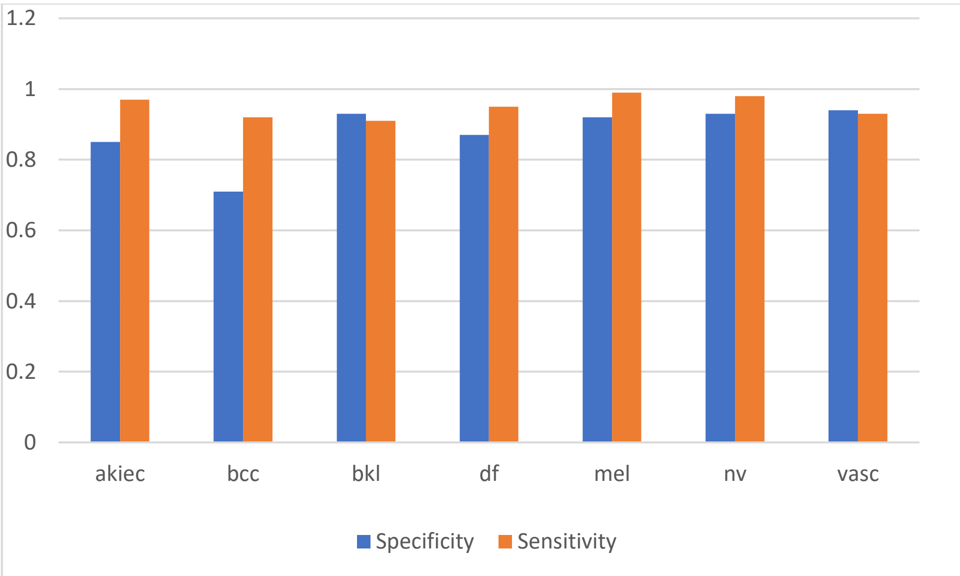


Fig.3 Sensitivity & Specificity

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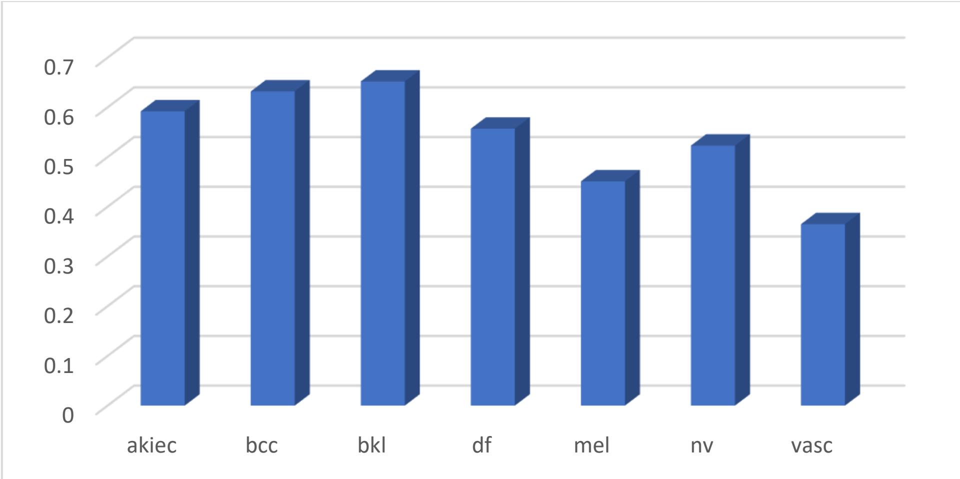
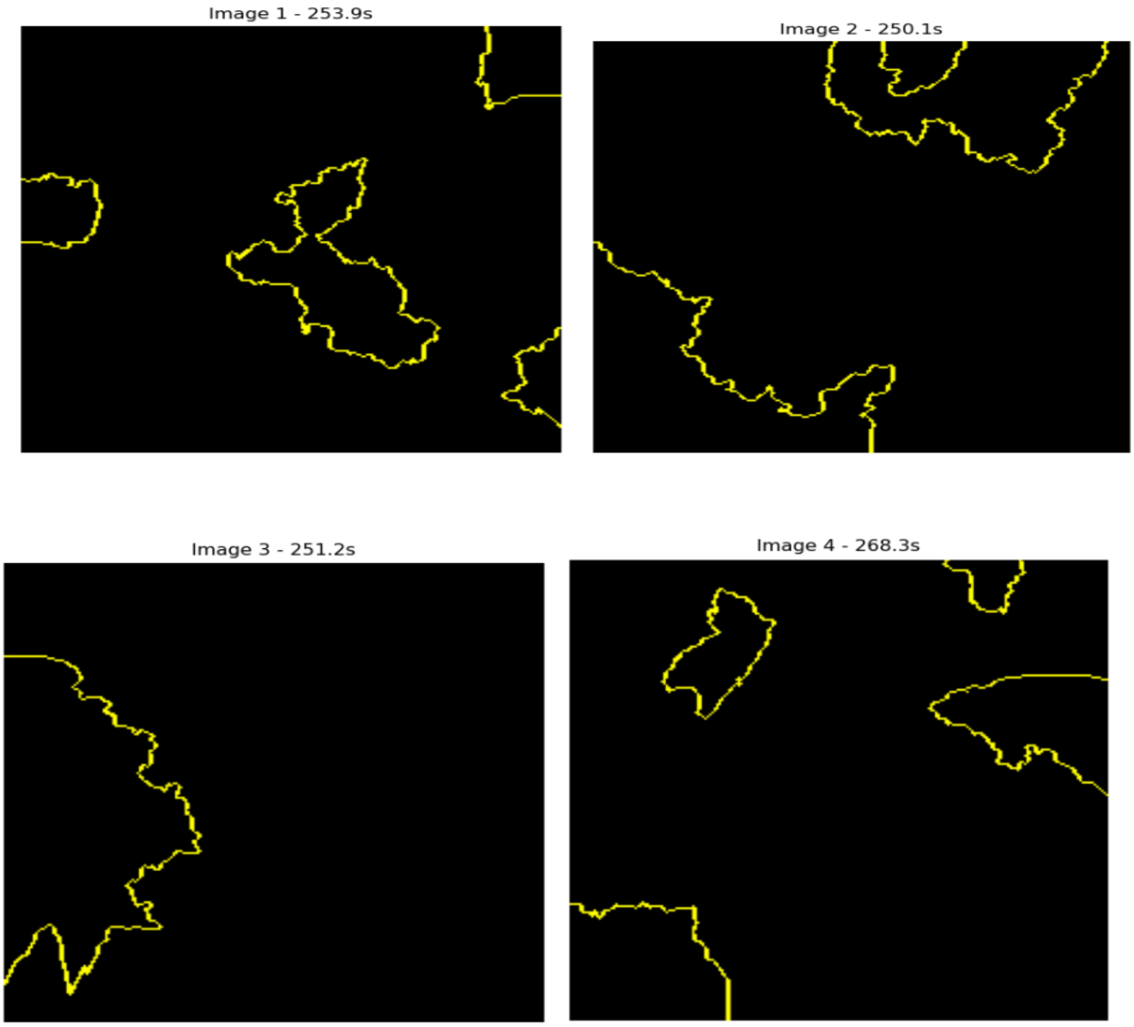



Fig.4 Loss

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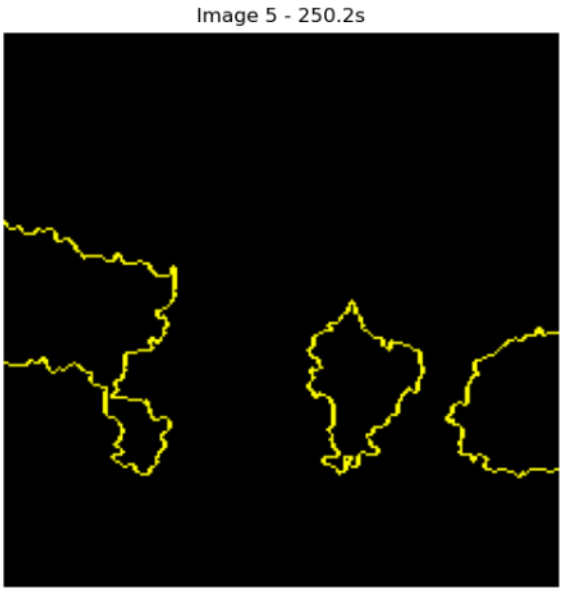


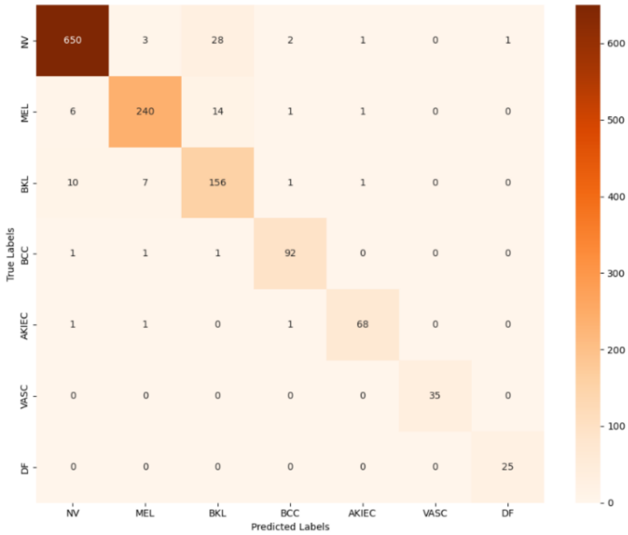


Fig.5 LIME Visualisation

Fig.6 Confusion Matrix for Parallel ResNet

## Conclusion

The proposed deep learning-based dual-branch classification system provides an efficient method to detect skin cancers in the early stages. The system combines two strong convolutional neural network structures ResNet50 and ResNet101 within a single framework to utilize their unique model capabilities for improving feature recognition and classification precision. The fusion of feature through concatenation, followed by fully connected layers, dropout, and batch normalization, ensures that the model is capable of learning complex patterns while minimizing the risk of overfitting. The system maintains transferable and generalized learned representations through freezing its pretrained convolutional backbone on the ImageNet dataset. Furthermore the model benefits from data preprocessing and augmentation through TensorFlow's ImageDataGenerator system when dealing with various kinds of skin lesions. The implementation of checkpointing features strengthens training persistence and operation continuity for interrupt scenarios. Deep learning models demonstrate their effectiveness through dual-model strategies since prediction fusion between different architectural designs improves both accuracy rate and overall robustness and decreases potential biases. This method shows strong potential to help dermatologists receive an exact tool for early skin cancer detection by fixing the shortcomings of existing diagnostic practices and specific predictive models. This proposed system delivers significant value to medical image analysis by providing a flexible and expandable technological solution for clinical medical applications. The proposed method uses Parallel ResNet architecture to perform effective feature extraction which leads to an accuracy of 95% in diagnosing skin cancer. It shows that the model is able to detect important features and offers good promise for clinical implementation.

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