A Universal Approach: Expanding the Diagnostic Power of This Model Beyond Skin Cancer

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Abstract. Within the fast-paced environment of artificial intelligence, deep learning algorithms have truly played a very special and important role in enhancing skin cancer detection; in fact, they may dramatically alter survival and early diagnosis rates. While most studies have focused on a single model of technique, our research utilizes a multi-framework model to optimize melanoma detection. In this study, we also combine Deep Convolutional Neural Networks VGG19(DCNN), VGG16, ResNet50, Capsule Networks (CapsNet), and vision transformers (ViT) for more profound images' features. Then the embedded features are fed into an ensemble model that involves five machine learning classifiers: Support Vector Classifier (SVC), XGBoost, Random Forest, K-Nearest Neighbors(KNN), and Logistic Regression via majority voting. This classification enhanced the accuracy of classification; ViT had attained its highest accuracy at 92.4%. The ensemble model we developed also performed well overall as it achieved 92.3% when used on a melanoma dataset. These results confirm that our ensemble approach significantly outmatch individual models and contributes more to the efficient detection of skin cancer.

Keywords: Melanoma Detection · CNN · ResNet50 · Vision Transformer(ViT) · CapsNet.

1 Introduction

Skin cancer, especially melanoma, that also referred to as one of the deadliest and most common cancers these days. It spreads aggressively which makes early diagnosis crucial. Traditional imaging, observational techniques, and biopsy are Consuming and prone to error, latest improvements in Machine Learning and Deep Learning technologies have improved diagnostic accuracy. According to dermoscopy, results show that in melanoma identification, convolutional neural networks work better. Kassani & Hosseinzadeh Kassani [1], 2019 conducted comparative analysis of the deep architectures for melanoma detection with a focus on clinically efficient architectures. Al-Masni et al.[2], 2019 found that the efficiency of the process in segmentation and classification of the lesion increased with the use of a combination of FrCN and residual networks. Current works focus on the improvement of melanoma detection with hybrid classic and deep learning models. Deep learning-based methods for melanoma diagnosis are shown to be promising by Jojoa Acosta et al. [4] (2021). According to Daghrir et al. [5](2020), a hybrid model of combining classical and Deep Learning techniques shows promising ability to accurately identify skin cancer. Other major contributions in 2020 by Sanketh et al.[9] and Rodrigues et al.[8] also reflect the possible application of CNNs in skin cancer detection, where in CNN based architectures surpassed the existing traditional methods of diagnosis. Inventions like deep-learning model-based image super-resolution methods, much increased the resolution of dermoscopic images and consequently improved diagnosis accuracy greatly, as conceptualized by Lembhe et al. [7] in 2023. Studies highlight machine learning's potential in dermatology for enhanced melanoma detection and improved patient out-comes.

2 Literature Review

Kassani and Hosseinzadeh Kassani [1] executed a comparison of various deep learning approaches for identifying melanoma using dermoscopic images. Among the studied models- AlexNet, VGGNet16, VGGNet19, ResNet50, and Xception- the best performance with an accuracy of 92.08% was shown by ResNet50. This study demonstrated that ResNet50, when combined with augmentation and preprocessing techniques, has significantly improved performance, making it suitable for accurate skin lesion classification. Al-Masni et al. [2] came up with an integrated model using a new combination of full resolution convolution networks (FrCN) for segmentation and residual network systems, namely ResNet-50 for classification. Later, this was extended to dermoscopy images with skin lesions segmented from the rest of the skin with 94.03% accuracy and obtained a Jaccard similarity coefficient of 77.11%. For the ResNet-50 model classification, accuracy attained 81.57%, with an F1-score of 75.75%. Such a combined approach enabled the ResNet50 to extract more number of specific features from segmented lesions and further enhanced skin lesion diagnosis compared to regular models. Albraikan et al. [3] developed an advanced model for melanoma detection that included a number of deep learning methods. Accordingly, the model in view for this research integrates K-means clustering for segmentation, a Capsule Network (CapsNet) with Adagrad optimizer for feature extraction, and Crow Search Optimization technique with the Sparse Autoencoder approach for the classification. A benchmark dataset tested this automated system with great classification accuracy, hence very promising in enhancing melanoma detection. Jojoa Acosta et al. [4] introduced a strategy that makes use of the Mask Region Based CNN (Mask R-CNN) for lesion segmentation and ResNet152 for classification. Their model reported an accuracy of 90.4%,and with 82% of sensitivity, and specificity of 92.5% in distinguishing malignant versus benign lesions. S jong, in essence, this can be a good combination with the current model for enhancing performance, as it will concentrate on the area of importance and deep feature mining for classification. Daghrir et al. [5] in 2020 have proposed one hybrid model for the detection of melanomas where deep learning is combined with classical machine learning methods. This paper used CNN, SVM, and KNN classifiers whose predictions combined through majority voting gave higher performance. Accuracy with CNN reached up to 85.5%, and the hybrid method further enhanced the accuracy to nearly 88.4% using a majority vote, thus justifying the point that integrated hybrid methods do give better results. Ghosh et al. [6] presented a hybrid ensemble model which includes deep learning embedded feature dimensions from the DCNN, Capsule Networks(CapsNet), and Vision Transformers. The next steps were to use machine learning classifiers after the concatenation of the feature vectors, and Logistic Regression, KNN, XGBoost, Support Vector Classifier(SVC), and Random Forest were employed through the mechanism of majority voting, yielding high accuracy of 91.6%. The ViT-based ensemble outperformed standalone DCNN and Caps-Net models by a margin, hence greatly improving melanoma detection classification performance. Lembhe et al. [7] (2023) investigated image super-resolution techniques to enhance the accuracy of deep learning models in skin cancer detection. In this study, low-resolution images were upscaled using InceptionV3, ResNet, and VGG16 models integrated with Image Super Resolution (ISR) and Generative Adversarial Networks (GANs). This was an approach that would enhance the skin lesions classification capability of the model. The use of ISR, therefore, coupled with GANs presents a promising future in enhancing diagnostic performance.Jose F. Rodrigues-Jr et al. [8], in their work entitled "DermaDL: Advanced Convolutional Neural Networks for Automated Melanoma Detection," proposed a new CNN architecture targeted for melanoma detection. This architecture was combined with state-of-the-art techniques such as Aggregated Transformations and Squeeze-and-Excite blocks. The result was that, without using general-purpose architectures, an AUC of 90% was achieved with their specialized network, beating the computational efficiency and melanoma detection accuracy for popular models like ResNet and VGG 5. Ravva Sai Sanketh et al. [9] (2020) proposed, in a research paper titled "Melanoma Disease Detection Using Convolutional Neural Networks," using convolutional neural networks for early detection of melanoma and non-melanoma skin cancers. They used the ISIC dataset and reported an accuracy of 91%. This CNN-based model outperforms the manual detection methodologies and tries to assist physicians with the correct classification of skin cancer without resorting to clinical procedures.

3 Proposed Methodology

3.1 Dataset Collection

This dataset was mined from the Kaggle [11] and is called the "Melanoma Skin Cancer Dataset of 10,000 Images." It contains 10,000 high-resolution dermoscopic images for identifying and diagnosing skin lesions that classified as malignant or benign. It trains an advanced deep learning model capable of differentiating benign conditions from the grave form of skin cancer-the melanoma.Train and Test Folders contain Benign and Malignant.This folder has 9,605 training images: 5,773 benign and 3,832 malignant, to train the model for differentiation.Total 1,000 images, split in equal proportions into 500 benign and malignant samples for model testing.Image enhancementing techniques like the rotation, flipping, and zooming are used. Preprocessing of data was done prior to sending it for training, thus improving the resolution and format to support better feature learning.

3.2 Preprocessing

Resizing These dataset images were uniformly resized to 128x128 pixel resolution. This preprocessing is important because it usually gives uniformity in the size of the images, a requirement that most deep learning models would want, including VGG16 and VGG19. It will reduce computational complexities, hence reducing training time without the loss of the essential features of an image.

Colorspace Conversion The images which are by default loaded through OpenCV are in BGR format. Since the deep learning models, implicitly expect input formatted as RGB, conversion of images to RGB color space was performed using the function cvtColor of the OpenCV library.

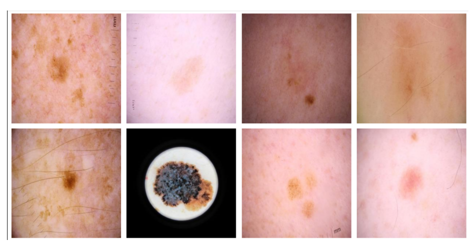


Fig. 1: Images before conversion

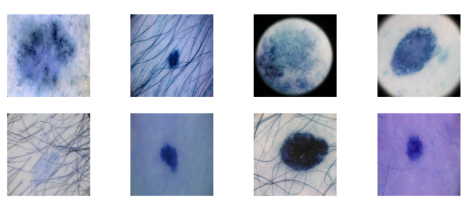


Fig. 2: Images after conversion

Shuffling This randomizes the presentation order of images across the benign and malignant classes. It reduces the amount of bias. Shuffling will make sure that, during training, changing patterns of images from both classes are seen by the model at regular instances, reducing the risk of overfitting on the early-patterned ones.

Normalization The Pixel values have been scaled to a range from 0 to 1 because all the RGB values have been divided by 255 to normalize the data within this range. Hence, model training will be faster because all the magnitudes of data are brought within the same range, and there is no saturation from the neural network's activation functions during training.

Label Encoding Categorical labels of the dataset, that is, 'benign' and 'malignant' were encoded into their numerical form in the first place. Label encoding hanges categorical data into integers-0 for 'benign' and 1 for 'malignant'. By doing so, all the algorithms understood what exactly these labels mean while training.

Train-Test Split Further, the preprocessed dataset was subsequently divided into two distinct subsets-testing 20% and training 80%. About 80% of the total data were put into the training set, while the remaining percentage of about 20% was kept for testing. This guarantees that a significant portion of the data is allocated for model training while it is being tested with unseen data so as to assess its ability for generalization and hence give good results for new inputs. This prevents the overfitting of data and thus gives a good measure of the performance of the model.

3.3 Models

This work follows the model approach hybrid deep learning with machine learning to classify melanoma images. In the proposed methodology, the deep learning model that has been pre-trained will be used for the feature extraction of images, while the actual classification is to be done through the machine learning model. Along with this, the approach also will employ an ensemble method to give better accuracy to the system. In detail, this will be briefed below:

Deep Learning architectures for Extracting Features

VGG16 and VGG19: We used pre-trained VGG16 and VGG19 models to extract image features. The network learns hierarchically; hence we could use them directly to extract good features for melanoma without retraining the whole deep network.

ResNet50: A pre-trained model learns the residual functions really well on deep structures by using skip connection. It performs well in the deep feature extraction for low and high level features of images.

Capsule Network: CapsNet strengthens spatial relations and recognizes complicated patterns. Unlike most convolution networks, its ability will be of recognizing part- whole relations, which has much significance in the detection of melanomas in skin lesions.

Transformer Vision ViT: The model uses the Vision Transformer, where self-attention captures global dependencies in input data. ViT is particularly efficient for image classification, this contribution well captures long- range dependencies, making it an ideal choice for this work.

Machine Learning algorithms for Classification tasks The following machine learning models are used for classification tasks after feature extraction

Logistic Regression: Logistic regression employs a linear model that sorts the images in some order by using extracted features.

Random Forest: Random Forest is an ensemble decision tree-based model that integrates multiple decision trees to provide useful classification for the target images.

K-Nearest Neighbors (KNN): KNN is a non-parametric distance-based classifier that compares test samples against their k-nearest neighbors within feature space.

Support Vector Classifier (SVC): SVC classifies the images using a kernel-based approach that seeks the maximum margin separation between classes, adopting a Radial Basis Function (RBF) kernel.

XGBoost: XGBoost is a gradient boosting machine learning model known for its efficiency and performance in classification tasks.

Ensemble Voting Classifier A number of model predictions are combined into a single prediction for better results using an ensemble voting classifier. This is achieved as: Individual predictions of VGG16, VGG19, ResNet50, CapsNet, and Vision Transformer are aggregated. The hard voting strategy was used; thus, the classification result depends on the majority vote of all the models. Hence, one advantage of this ensembling technique is that the inherent variance and bias of single models are reduced in an attempt to give better overall accuracy. It is a model that has been trained by the proposed approach on the melanoma dataset. Some of the metrics for the assessment of the performance of the model includes F1 score, recall, precision, and the accuracy. In that regard, higher results were allowed to the classifier with ensemble voting in comparison with individual deep learning and machine learning models that proved the validity of the approach presented.

4 Proposed Model

The proposed Vision Transformer (ViT) model used attention mechanisms for long-range dependencies in image classification. The input shape is (128, 128, 3) with four transformer blocks, an embedding dimension of 32, and eight attention heads. A feed-forward and drop-out of 0.1 prevent overfitting and enhance classification based on feature points.

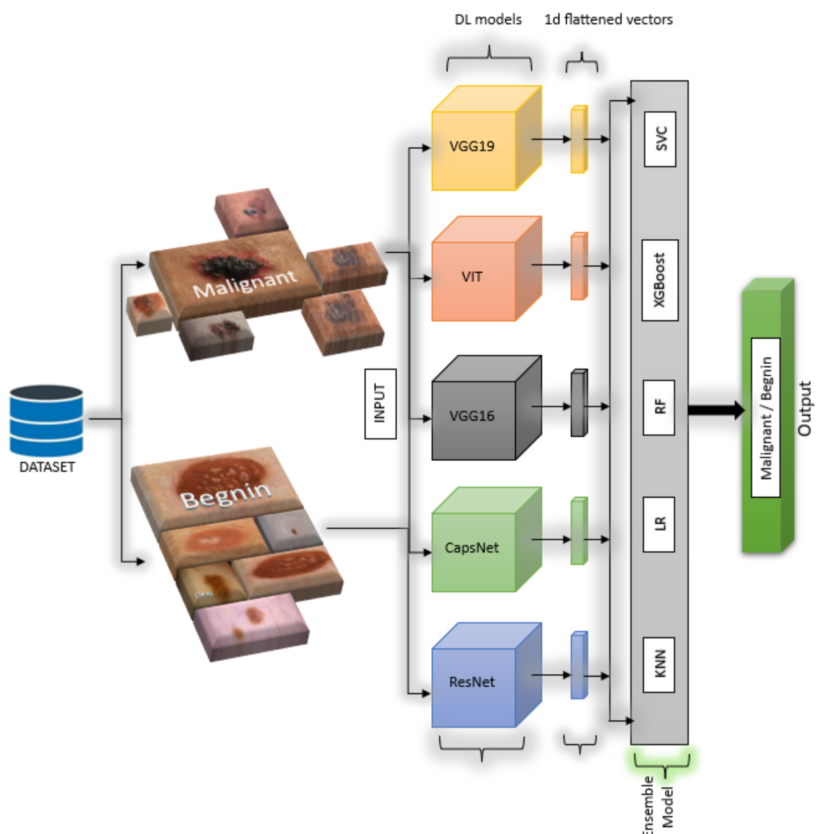


Fig. 3: Proposed Architecture for Melanoma Detection Using Vision Transformer.

Utilizing Adam-Adaptive moment estimation algorithm, learning a rate of 0.0001 has been set for multi-class classification with sparse categorical cross-entropy loss function is used ,with a Batch size of 32 per epoch and is tunable for best performance. Regulation at 0.0005 and max norm of 5.0 avoids overfitting and enhances generalization. The accuracy in ViT was 0.924, and recall, precision and F1 scores were the same in testing. A fair metric indicates that an accurate model balances both true positives and negatives with the least amount of bias. It classifies test images based on the actual ground truth labels. The metrics are computed and the correspondences in t-SNE coupled with the confusion matrices analyze classification strengths as well as improvement areas.

Table 1: Transformer Model Architecture Parameters.

Parameter	Value
Input Shape	(128, 128, 3)
Number of Transformer Blocks	4
Embedding Dimension	32
Number of Attention Heads	8
Feed-Forward Dimension	32
Dropout Rate	0.1

Table 2: Training Setup.

Parameter	Value
Optimizer	Adam (learning rate: 0.0001)
Loss Function	Sparse Categorical Cross-Entropy
Batch Size	32
Regularization Parameters	0.0005
Max Norm	5.0

5 Analytical Comparison

Various machine learning models and deep learning models were analyzed in this work to detect melanoma skin cancer. The different models that have been tried in this work include KNN, Logistic Regression, Random Forest, XGBoost, SVC, Ensemble models, and deep learning models includes VGG 19, VGG 16, ViT, ResNet50, and CapsNet. All these models are assessed based on their performance by considering the precision, recall score, accuracy and F1 score.

5.1 Performance Table

Table 3 gives all models performance. Vision Transformer ViT stands the best among all models with 92.4% accuracy. Following ViT, VGG 19 with 92.2% then VGG16 with 91.7% and at last ResNet50 and CapsNet with 90.6% and 90.3% respectively.

Table 3: Accuracy Comparison of Various Models.

Model	Accuracy
VGG19	92.2%
VGG16	91.7%
CapsNet	90.3%
ViT	92.4%
ResNet50	90.6%

5.2 Training and Testing Accuracy Graphs

Comparing the training and testing accuracy graphs of VGG19, VGG16, CapsNet, ViT, and ResNet50. VGG19 reached 92.2 training accuracy with strong feature extraction and low overfitting, while VGG16 lagged at 91.7% with lower effectiveness and more loss. It achieved 90.3% accuracy, surpassing VGG models due to CapsNet's better spatial hierarchy capture, though it required more epochs to stabilize. ViT reached 92.3% accuracy with long dependency attention and was initially slow but matched others in generalization and robustness. ResNet50 scored 90.6% accuracy, providing stability and outperforming ViT and VGG19.

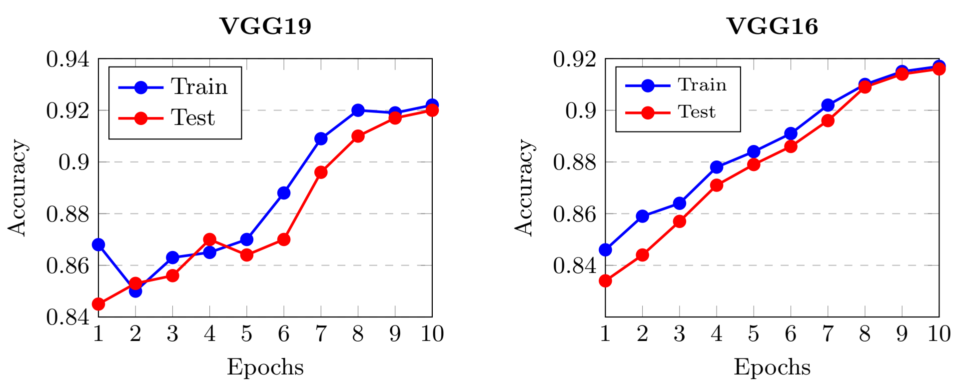


Fig. 4: Training and Testing Accuracy graphs of all models

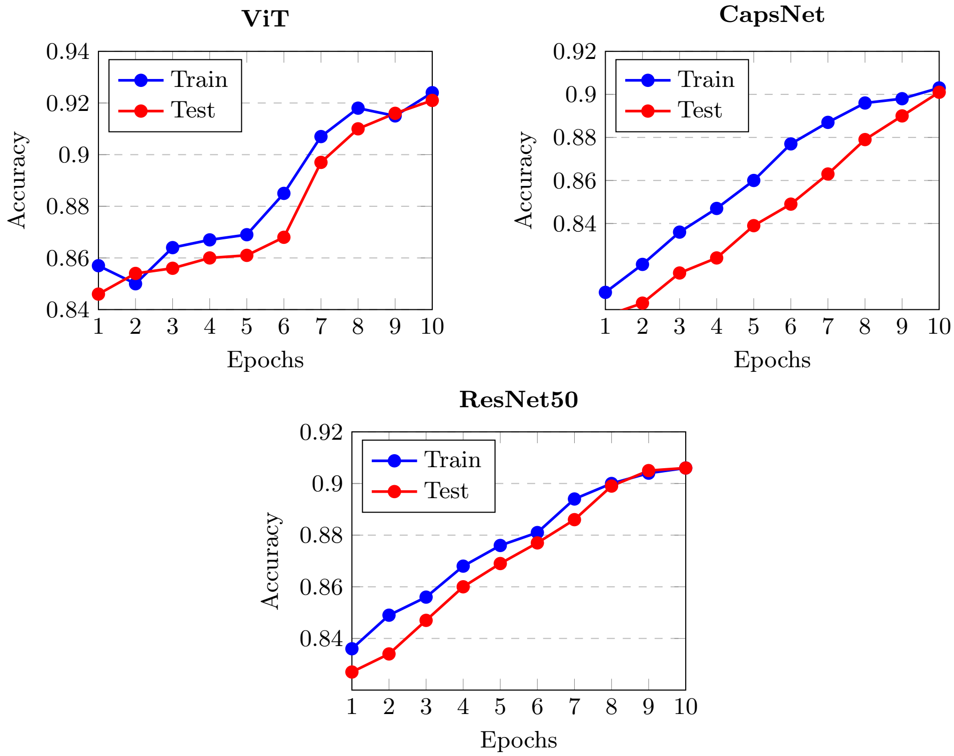


Fig. 5: Training and Testing Accuracy graphs of all models

5.3 Evaluation Metrics

Below Table 4 is the evaluation matrix for all models: comparing all the models across the metrics precision,recall,f1 score and accuracy. In Table 4, the most critical metrics include accuracy, precision, recall, and F1 score, which emphasizes the ability of each model to accurately detect melanoma. Accuracy measures overall correct classifications; hence, both ViT (92.4%) and Ensemble (92.3%) have robust performance in correctly classifying benign and malignant cases. Precision indicates each model's ability to avoid false positives and thus avoid unnecessary treatments, where ViT is strong with high precision. Recall (sensitivity) means fewer false negatives, that is fewer missed melanomas, and ViT does well with a recall of 92.4%. The F1 score, a measure of finding the balance between precision and recall, is also in favor of ViT and Ensemble to classify with a good accuracy and balance. CapsNet and ResNet50 promise to do better in complex feature detection but slightly lower F1 scores indicate some compromise between false positives and false negatives. The comparison once again establishes ViT for high-stakes medical diagnosis.

Table 4: Comparison of Models Across Metrics

MODEL	Metric	Vgg19	Vgg16	CapsNet	ViT	ResNet
KNN	ACC	91.7	91.1	90.4	91.9	90.5
	PRE	91.7	91.1	90.4	91.9	90.5
	REC	91.7	91.1	90.4	91.9	90.5
	F1	91.7	91.1	90.4	91.9	90.5
LR	ACC	90.7	91.2	90.3	92.2	90.9
	PRE	90.7	91.2	90.3	92.2	90.9
	REC	90.7	91.2	90.3	92.2	90.9
	F1	90.7	91.2	90.3	92.2	90.9
RF	ACC	91.3	91.2	90.4	89.5	90.8
	PRE	91.3	91.2	90.4	89.5	90.8
	REC	91.3	91.2	90.4	89.5	90.8
	F1	91.3	91.2	90.4	89.5	90.8
XGBOOST	ACC	92.3	91.5	90.2	91.9	90.5
	PRE	92.3	91.5	90.2	91.9	90.5
	REC	92.3	91.5	90.2	91.9	90.5
	F1	92.3	91.5	90.2	91.9	90.5
SVC	ACC	91.4	91.0	90.3	92.4	90.6
	PRE	91.4	91.0	90.3	92.4	90.6
	REC	91.4	91.0	90.3	92.4	90.6
	F1	91.4	91.0	90.3	92.4	90.6
ENSEMBLE	ACC	92.2	91.7	90.3	92.3	90.6
	PRE	92.2	91.7	90.3	92.3	90.6
	REC	92.2	91.7	90.3	92.3	90.6
	F1	92.2	91.7	90.3	92.3	90.6

5.4 Model Summary

The Table 5 provides an overview of the models applied for melanoma detection, highlighting their parameters and computational complexities. VGG19 and ResNet50 stand out for their high parameter counts (20 million and 23.5 million, respectively), indicating robust architectures with significant feature extraction capability. VGG16 is simpler with 14.7 million parameters, making it slightly faster but with a marginally reduced feature set. CapsNet, with approximately 7 million parameters, utilizes capsule layers for improved spatial awareness, beneficial for detailed lesion detection. ViT, with only 218,946 parameters, is highly efficient; it leverages self-attention mechanisms to capture image dependencies, achieving high accuracy with minimal computational cost.

Table 5: Model Parameters Comparison.

Model	Parameters
VGG19	20,024,384
VGG16	14,714,688
CapsNet	7 million (approx)
ViT	218,946
ResNet50	23,587,712

5.5 Model Parameter Tables

Table 6 provides the parameters of the VGG19 and VGG16 models outline their design and functional differences. Both models accept input images of shape (128, 128, 3) and include fully trainable layers, allowing for comprehensive feature extraction from dermoscopic images. The base models, VGG19 and VGG16, are similar in architecture, but VGG19 has additional convolutional layers, resulting in a total of 20 million parameters compared to 14.7 million in VGG16. This added complexity allows VGG19 to capture more detailed patterns but also increases computational demand. For feature extraction, both models output a standardized shape of (9605, 512), which aids in efficient downstream classification.

Table 6: Comparison of VGG19 and VGG16 Models.

Parameters	Value(VGG19)	Value(VGG16)
Input shape	(128,128,3)	(128,128,3)
Base Model	VGG19	VGG16
Trainable Layers	True	True
Feature Extraction Shape	(9605,512)	(9605,512)
Standardize Features Shape	(9605,512)	(9605,512)
Number of Classes	2	2
KNN Neighbors	10	10
Random Forest Estimators	50	50
XG Boost Tree Method	Auto	Auto
SVC Kernel	RBF	RBF
SVC C	0.65	0.65
Voting Classifier	Hard	Hard

The ResNet50 model in Table 7, with 23.5 million parameters and trained on ImageNet weights, utilizes skip connections to manage deep layers efficiently. Its robust architecture excels in extracting both high-level and low-level image features, making it well-suited for detailed melanoma analysis.

Table 7: Parameters for the ResNet50 Model.

Parameter	Value
Input_shape	(128,128,3)
Num_classes	3
Number of parameters	23,587,712
Optimizer	adam
Loss Function	categorical crossentropy
Epochs	10
Batch_size	32

CapsNet in Table 8 employs approximately 7 million parameters with a unique capsule structure that captures spatial hierarchies, improving pattern recognition in skin lesions. Its architecture includes dynamic routing, which enhances the model's accuracy in distinguishing subtle features within dermoscopic images.

Table 8: Table of Parameters for CapsNet.

Parameters	Value
Input_shape	(128,128,3)
Num_classes	3
Conv1_filters	256
Conv1_kernel_size	9
Conv1_padding	Valid
Primary_caps_dim	8
Primary_caps_n_caps	32
Primary_caps_strides	2
Conv_caps_dim	16
Conv_caps_n_caps	32
Conv_caps_kernel_size	9
Conv_caps_padding	Valid
Dense_caps_dim	16
Dense_caps_n_caps	3
Decoder_network	[512,1024,784]
Optimizer	Adam
Learning_rate	0.0001
Epochs	10
Batch_size	32

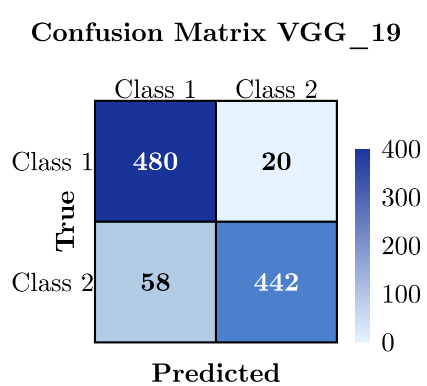
The Vision Transformer (ViT) model in Table 9, with 218,946 parameters and four transformer blocks, is highly efficient in processing images through self-attention mechanisms. Despite its compact size, ViT's ability to capture long-range dependencies enables it to achieve high accuracy with minimal computational cost.

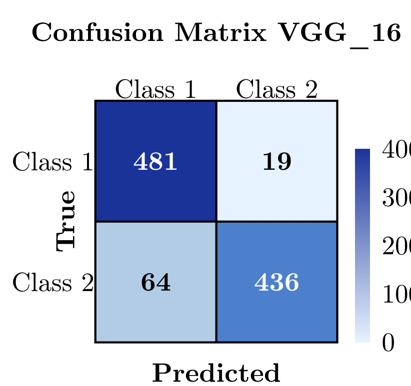
Table 9: Parameters for the ViT Model.

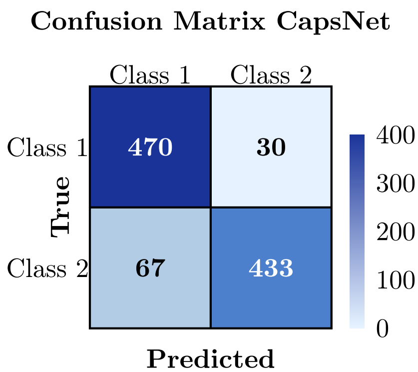
Parameter	Value
Input_shape	(128,128,3)
Num_classes	2
Num_transformer_blocks	4
Embed_dim	32
Num_heads	8
Ff_dim	32
Dropout	0.1
Optimizer	Adam
Learning_rate	0.0001
Epochs	10
Batch_size	32
Regularization_scale	0.0005

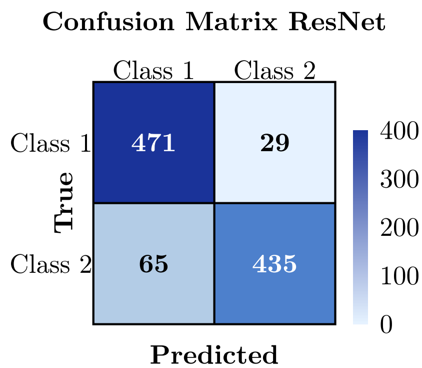
5.6 Confusion Matrix

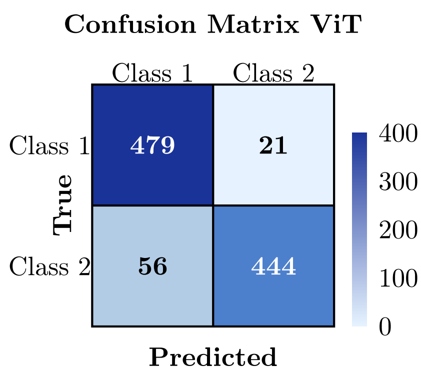
We compared the confusion matrixes of deep models such as VGG19, VGG16, CapsNet, ViT, and ResNet50 and visually identify the true positives, true negatives, false positives, and false negatives. VGG19 balances TPs and TNs well but has occasional FPs due to benign misclassifications. VGG16 shows a similar pattern but with more FNs, indicating potential melanoma misses. CapsNet's feature hierarchy boosts TPs but may increase FPs due to spatial emphasis. ResNet50 maintains low FPs and balanced TPs/TNs with its skip connections, reducing misdiagnoses. ViT achieves the highest accuracy, minimizing both FPs and FNs through its self-attention for complex dependencies, making it highly effective for melanoma detection.











6 Conclusion

Our paper comes with an innovative method that aims to improve melanoma detection by deep learning models VGG19 and VGG16, ResNet50, Vision Transformer (ViT), and CapsNet. Ensemble techniques by combining DL with ML classifiers XGBoost and SVC result in good outcomes, including being one of the top-scoring models from the ensemble ViT model. This study employed the Vision Transformer (ViT) model along with CNN architectures such as VGG19, VGG16, ResNet50, and Capsule Networks to improve melanoma detection accuracy. Among these, the ViT model achieved the highest accuracy at 92.4%, highlighting its strength in capturing global image features essential for identifying melanoma patterns. ViT's self-attention mechanism enabled it to focus on critical areas of images and capture dependencies often missed by CNNs, leading to higher precision, recall, and F1 scores. A notable recall score indicated effective true-positive identification, crucial for early, reliable skin cancer diagnosis. Ensemble method by combining ViT with other models through majority voting improves robustness to 92.3%. This ensemble has balanced local and global feature extraction, which increased the overall classification accuracy. The Vision Transformer performed well in this task, especially as part of an ensemble. In fact, the findings show that ViT, combined with CNNs, has much potential in image-based diagnostics, and using hybrid CNN-ViT models can improve performance even more in the future. This work not only contributes to melanoma detection but also serves as the foundation for more generalized applications in the clinical sector. More research can be based on these directions in other medical domains by modifying these models to adapt to other medical imaging tasks and encourage close collaboration with medical specialists as well as proper bedside integration and applicability in real-world medical scenarios. Such results therefore mean new models of performance testing and even working together with doctors open a wide range of huge opportunities in the use of AI for medical purposes beyond the example of merely diagnosing skin cancer.

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