https://doi.org/10.48047/AFJBS.6.12.2024.1374-1385

AFJBS African Journal of Biological Sciences
Journal homepage: http://www.afjbs.com

Research Paper Open Access

MELANOMAIMAGE CLASSIFICATION AND DETECTION USING MULTI-CLASS DEEP LEARNING NETWORK MODELS

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Article History
Volume 6 Issue 12, 2024
Received: 25 May 2024
Accepted : 25 June 2024
doi:
10.48047/AFJBS.6.12.2024.1374-1385

Abstract:
Skin cancer that evolved in melanocytes, and early identification is crucial due to its ability to unfold. Proposed research affords a unique technique to cancer detection using deep gaining knowledge of methods and switch mastering methodology. Convolutional neural networks (CNNs) are proposed as a possible approach for distinguishing benign from malignant pores and skin lesions. It evaluates overall performance in pores and skin lesion categorization the usage of four alternative deep mastering architectures such as MobileNetV2, ResNet50, InceptionNetV3, and VGG19. Proposed study exceptional-tunes and trains fashions using a numerous variety of dermoscopic pictures a good way to obtain accuracy, computational performance, and processing speed for actual-world clinical use. In this research additionally highlights the influence of version structure on classification metrics which affords treasured insight into the satisfactory line among accuracy and use of computation aid in pores and skin lesion prognosis.
Keywords:CNN,InceptionNetV3, Melanoma, MobileNetV2, ResNet50, VGG19.

1. Introduction:

Skin cancer, including non-melanoma and malignant melanoma, is a serious and growing global public health issue. Cases of both kinds have increased recently some research indicates that the prevalence of both conditions doubled between (Li, Yuexiang, and Linlin Shen. (2018) 1970s and 1980s. Skin malignancies other than melanoma, such squamous cell carcinoma and basal cell carcinoma, are often not lethal but may need to be surgically removed, which might result in invasion and deformity. Long-term, repetitive UV radiation exposure is mostly to blame for this rise in occurrence, which mostly affects the face, neck, forearms, and other body areas.

A wide variety of genetic background, individual characteristics, and patterns of UV exposure constitute risk factors for malignant melanoma. Other major predisposing traits include white skin, blue eyes, red or blond hair; atypical moles (nevi), which occur more frequently in light-skinned populations, are the main determinants of disease incidence. Experimental data reveal that melanoma patients are particularly sensitive to solar UV radiation. This is especially true for those with a high or intermittent history of sun exposure and early sunburn. In addition, the distribution of malignant melanomaHasan, M. R et. Al.,(2021) shows a marked geographic gradient with higher rates recorded at lower latitudes, as seen in Australia with a disproportionately higher rate compared to Europe. However, cumulative sun exposure remains a controversial risk factor, while a past history of non-melanoma skin cancers and solar keratoses, which indicate chronic UV damage are quite strongly associated with an increased likelihood of melanoma.

One of the environmental variables that will increase the occurrence of pores and skin most cancers as a result of extended UV radiation is ozone depletion. It is predicted that the ozone layer could thin, which might result in a upward push in skin most cancers occurrence globally. Furthermore, it appears that a few individual behavior, such leisure tanning and beyond burn enjoy, are modifiable danger elements, highlighting the need of public fitness campaigns and preventative efforts. Conversely, demographic factors are intently linked to susceptibility; those with truthful pores and skin tones are far much more likely to be susceptible than people with darker pores and skin tones. Some high-chance corporations may be diagnosed with the aid of some causal factors, which include; lighter skin, lighter eye or hair colour, liable to sunburn, lots of marks on the frame**,** Likhar, K., &Ridhorkar, S. (2024)**,** and additionally a family history of ever having skin cancer. However, it need to be remembered that all kinds and sorts of skin are susceptible to solar harm, for this reason emphasizing its usual significance regardless of pores and skin coloration.

Melanoma is the main health problem around this sector because it results in malignant melanocyte turnover. For example, about 650,150 new melanomas could be identified in the United StatesGupta, P., &Mesram, S. (2022)throughout the year 2024 if men accounted for differently than women. Despite advances in therapeutic approaches leading to progressive survival, cancer remains an excellent prostate cancer site and skin cancer mortality rate.

It makes a difference in the development of cancer, age- and sex-specific feedback, complicating it Given that the set of younger girls and pick-ups from extra younger guys are decreasing In the early 2000s. But in the same among older women, the bill has doubled Time as the ultimate complex in adults. Notably, cancer has standards of loss of life From 2014 to 2016 there was a sudden decline, mainly due to improvements in manufacturing, . receiving annual discounts of between 5% and 8%. the risk of cancerKaur, R et al., (2022). Mostly triggered by the use of small vessels and veins and skin pigmentation, which is dangerous for life generates ideas in tribal and ethnic organizations. However, while the typical age of evaluation is 68, most cancers are not always rare in people younger than 30. It is among one of the most common cancers in adolescent girls, especially women. Individual risk factors, such as age, genetics, and environmental factors interventions, likewise contribute to the complex picture of cancer The sensation of feeling.

Advancements in deep getting to know, this paper embarks on a comparative exploration of 4 distinguished deep studying architectures—MobileNetV2, ResNet50, InceptionNetV3, and VGG19—for the type of pores and skin lesionsKaur, Ret,al., (2022). By examining the performance and efficacy of those fashions, this look at seeks to offer valuable insights into their suitability for correct and green pores and skin lesion prognosis. In current years, deep gaining knowledge of fashions have established first-rate competencies in severapicture class responsibilities Dildar, M et.al., (2021), collectively with scientific imaging. With the proliferation of pores and pores and skin lesion datasets and improvements in neural community architectures, there may be growing interest in leveraging these technology for automated pores and skin lesion type. By harnessing convolutional neural networks (CNNs), the ones models can examine tricky stylesKhan, I.et,al., (2021) and capabilities inherent in skin lesion images, facilitating correct and reliable elegance consequences.

The Models under investigation—MobileNetV2, ResNet50, InceptionNetV3, and VGG19—represents a variety of architectural designs, each with its own strengths and qualities. It is known as MobileNetV2 for example functionality and compactness, making it ideally suited for those with limited resources The environment. On the other hand models like ResNet50 and VGG19 are venerable Their depth is the abilityKhan, I.et,al., (2021) to understand complexity, albeit at a cost related to computer hardware. after For a comprehensive review of MobileNetV2, ResNet50, InceptionNetV3, and VGG19Radhika, V and Chandana, B. S. (2023)**.** Skin lesion classification, it is clear that each example holds unique strengths and qualities. but based on standards of accuracy In terms of operational efficiency, as well as computational efficiency, ETA stands out as a model The best option available.

Many of the researchers conducted a comparative study of skin lesion images by Intensive learning strategies. Different models have been used, e.g. However, AlexNet, ResNet50, VGG16, Xception, MobileNet, and. Effective networking. With each passing year, technological advances are introduced innovation and development. Additionally, CNN imagery continues to improve, introduction of brand new construction or renovation of existing ones. The dynamic landscape highlights new trends in the industry Applied deep learning to medical image analysis.

In private et al., [2022] performed a landmark study where they were distributed Images of skin lesions, captured by a camera, fall into three obvious categories: Nevus, seborrheic keratosis. This was a division of labor It was developed using AlexNet's pre-trained and enhanced iterations and DenseNet-121 convolutional neural network (CNN) algorithms[7]. The rationale behind the selection of these CNN images was based on the exposure effective in different areas. A pioneering approach was introduced by Asad Ullah et al., [2022], wherein a novelGupta, P., &Mesram, S. (2022)hybrid model amalgamating ResNet50 and VGG16 classifiers was presented. Central to their methodology was the implementation of requisite data pre-processing techniques, alongside the strategic application of down-sampling to ensure dataset balance. Leveraging this balanced dataset, the researchers conducted comprehensive training and testing routines, aiming to classify input images into distinct categories: Melanoma and Non-Melanoma.

Ridhorkar, S et al., [2024] proposed an ensemble model combining VGG-16, VGG-19, and Inception V3 for skin cancer identification. Through comparative analysis, we find VGG-16 outperforms with 92% accuracyGupta, P., &Mesram, S. (2022)**,** excelling in sensitivity, accuracy , F-Score , specificity , false-positive rate and precision. Our research highlights the potential of ensemble models in enhancing early cancer diagnosis where by vgg 16 plays a pivotal role .

Hasan, M. Et al., [2021] took a holistic look at a range of CNN models including those that are pre-trained such as VGG16, ResNet50 and Support Vector Machine (SVM) as well as home-made sequential ones. To identify the most effective model for classifying benign and malignant skin cancer images from a Kaggle dataset with 6594 samples, this study examined their fantastic functioning mechanisms and layer variations. The results showed that VGG16 reached the highest accuracy of 93.18% which was better than SVM, ResNet50; and Sequential models among other things.

There was an project by Monirujjaman Khan, M. Et al., [2023] to create a diagnostic system Sherif et.al., (2019) that is automated for classifying melanoma the usage of dermoscopy photographs. Different pre-trained models and strategies of transfer studying have been involved in this hobby. To differentiate between benign and malignant pores and skin lesions for cancer identity, shape, length and coloration homes had been used as parameters. ResNet101, DenseNet, EfficientNet and InceptionV3 are a number of the trained models.

In their 2022 study, Kaur et al.,(2022) hope to create a very effective deep learning network that can differentiate between benign tumors and melanoma. The model has several linked blocks that allow feature information to flow smoothly. The capacity for feature extraction is increased by repeatedly using sub-blocks with particular ratios to maximize the depth of the network. To extract low- and high-level feature information from skin lesions, each block is meticulously constructed utilizing parameters such as kernel number, filter size, and stride. The suggested model is a lightweight and reliable approach to classifying skin cancer since it outperforms cutting-edge techniques on the ISIC datasets, obtaining more accuracy and using fewer parameters.

A unique framework for the recognition of dermoscopy pictures is presented by Gaikwad, M., et al. (2020). It makes use of deep learning techniques together with a local descriptor encoding scheme. Firstly, an extraordinarily deep residual neural network, pre-trained on a huge natural picture dataset, is used to extract deep representations of rescaled dermoscopy images. The global picture representation is then constructed by utilizing orderless visual statistic features based on Fisher vector encoding Dildar.M.et.al.,(2021) to collect local deep descriptors. Lastly, melanoma picture classification is achieved by the use of a convolutional neural network (CNN) and the Fisher vector encoded representations. Even with a minimal amount of training data, our suggested technique has the potential to produce more discriminative features, efficiently handling significant differences within melanoma classes and tiny variations between melanoma and non-melanoma classes.

3. Methods and Methodology:

3.1 Materials and Tools:

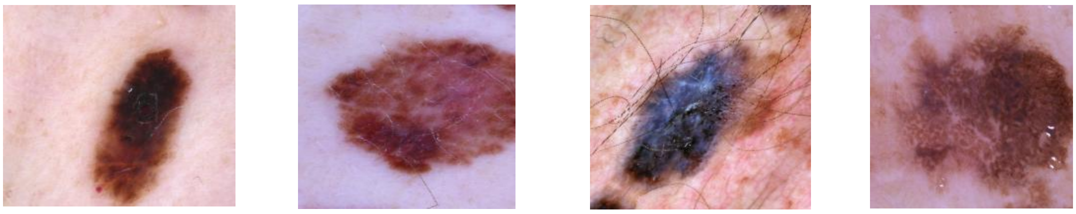
This study uses PyCharm 2023.2 with Python 3.10 in order to do in-depth data analysis and model creation. Because of the extensive library available for Python, particularly for deep learning issues, it has become the most often used programming language in data analysis. The installation of TensorFlow allows for highly developed machine learning algorithms through the use of dataflow programming. Computational tasks will run well while using a laptop with a core i5 CPU, 8 GB of RAM, and a 2 GB GPU integrated in. In an effort to advance deep learning and data analysis applications with professionalism, PyCharm centralizes project management for more structured and effective development.

3.2 Dataset Description:

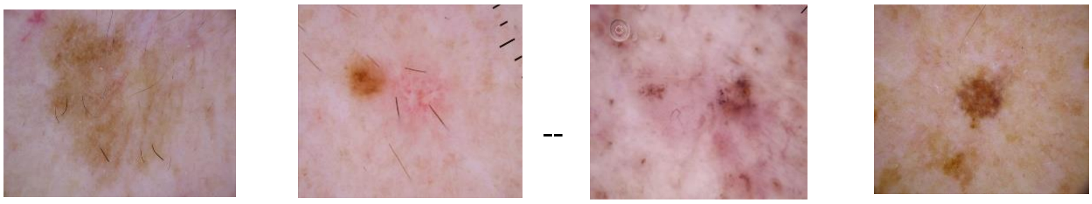
The "Melanoma Detection Dataset" is designed to detect cases of non-melanoma skin diseases and melanoma, a malignant type of skin cancer defined by aberrant development of melanocytes. Non-melanoma illnesses include a variety of benign growths and skin problems, whereas melanoma is characterized by irregular, asymmetric lesions that vary in size and color. This dataset provides a comprehensive repository for training and assessing melanoma detection algorithms, with 3920 photos of melanoma and 2450 images of non-melanoma lesions. Because of its evenly distributed picture set, which guarantees reliable performance evaluation, dermatological imaging studies for precise diagnosis and therapy are advanced.

Table 1: Distribution of Images in Melanoma and Non-Melanoma Classes

S.No	Class Name	No. of Images	Training images	Testing images
1.	Melanoma	3920	3136	784
2.	Non-Melanoma	2450	1960	490



--Melanoma--



Non-Melanoma--

Fig. 1. Malignant & Benign Images

3.3 Proposed System Methodology

The method used for skin lesions classification involves a complete assessment of four distinct deep learning models: ResNetV2, InceptionNetV3, MobileNetV2, and VGG19. Each model's architecture is configured with standard data preparation processes that also include picture directory definition, resizing images, and preparing the data. Fine-tuning is conducted if appropriate to improve performance with a particular transformation of some model layers. Custom classification layers are afterward implemented on top of the included models and model compilation conducted using normal optimization and loss functions. Subsequently, training with pre-established generators is conducted, where the models have similar number of epochs, early stopping, and learning rate modification routines.Evaluation metrics such as precision, recall, F1 score, and accuracy are computed using sklearn functions to gauge each model's classification prowess. Further, trained models are stored and reloaded for prediction tasks, while image preprocessing functions are established to facilitate accurate predictions. Throughout the evaluation process, key metrics including training/validation accuracy, loss, and confusion matrix are graphically represented, enabling a comprehensive comparative analysis of the models' performance in skin lesion classification. Additionally, the option for post-training fine-tuning is available to optimize model efficacy further.

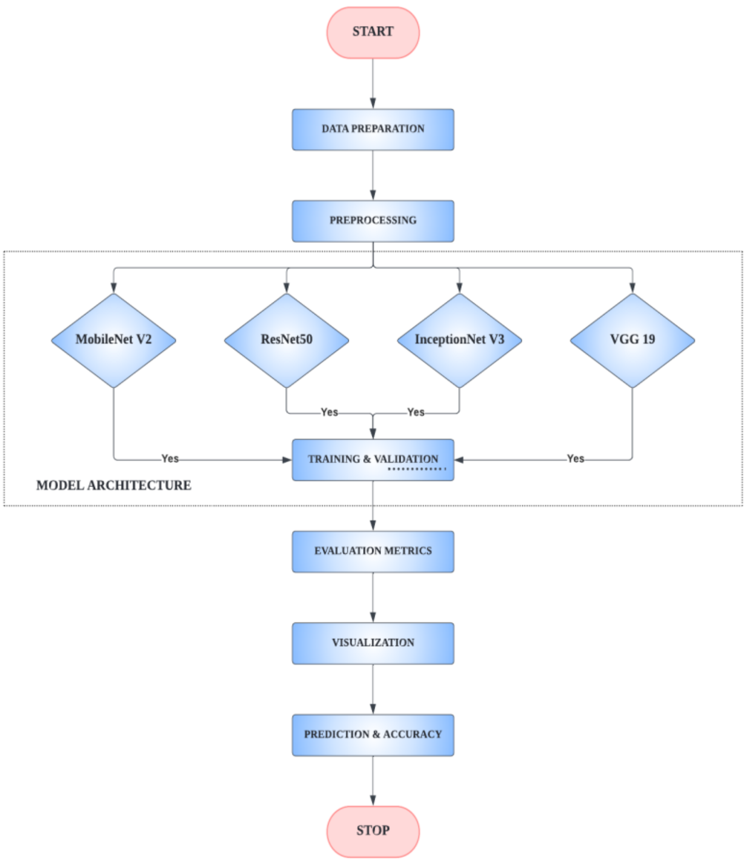


Fig. 2. System block diagram

3.4 Model Architecture

3.4.1 Convolutional Neural Network

Convolutional Neural Networks (CNNs) stand as a pinnacle in the domain of image recognition and classification, heralding a new era in real-time applications such as robotics and autonomous vehicles. Their unparalleled prowess in discerning faces, pedestrians, traffic signs, and myriad other visual elements transcends human capabilities, rendering them indispensable in modern technological landscapes. Rooted in the tenets of supervised learning, CNNs harness the power of labeled data to decipher intricate relationships between input objects and their corresponding class labels. At the heart of CNN architecture lies its hidden layer, meticulously crafted with a convolutional layer, pooling layer, and activation function, offering a streamlined training process owing to its judiciously reduced parameters and model intricacy.The convolutional layers, epitomizing the quintessential building blocks of CNNs, orchestrate a symphony of convolutional kernels meticulously engineered to weave intricate output feature maps from raw input data.

Each convolutional operation, akin to an artisan's brushstroke, delicately unveils hidden nuances and salient features embedded within the visual tapestry. Furthermore, the pooling layers, following in the footsteps of their convolutional counterparts, deftly curate compact representations of feature maps through strategic subsampling, deftly preserving vital information while gracefully reducing dimensionality. Techniques such as max-pooling and average-pooling, akin to virtuoso performances in the realm of data compression, ensure the model's resilience against the siren call of overfitting, fortifying its capacity for robust generalization.In the denouement of the CNN narrative lies the fully connected layer, a bastion of classification prowess wherein extracted features converge to sculpt a definitive classification landscape. Through an intricate web of interconnected neurons, each pulsating with the essence of learned features, the fully connected layer navigates the labyrinth of abstract representations to distill complex visual stimuli into crystalline classifications. Yet, within the intricate tapestry of CNN architecture, not all layers bear the mantle of full connectivity. This judicious restraint, a testament to the artistry of network design, strikes a harmonious balance between computational efficiency and the model's acumen for deciphering multifaceted patterns, thus cementing CNNs as indispensable instruments in the pantheon of image analysis and classification.

The model in this paper incorporates, Convolutional Layersemployed in MobileNetV2, ResNet50, InceptionNet V3, and VGG19, play a crucial role in feature extraction, discerning essential patterns like edges and textures from input images. Following convolution, the Global Average Pooling Layer condenses feature maps, reducing model parameters and enhancing inference speed. Subsequently, Dense (Fully Connected) Layers analyze these features for classification, utilizing activation functions like ReLU and softmax to distill complex visual stimuli into distinct categories. To combat overfitting, Dropout Layers are integrated, randomly deactivating neurons during training to improve generalization. Additionally, Batch Normalization stabilizes training dynamics by normalizing activations at each batch, ensuring smoother convergence and faster learning.

These architectural elements collectively contribute to the effectiveness and efficiency of convolutional neural networks in various image recognition tasks.

3.4.2 MobileNet V2

A neural network architecture called MobileNetV2 was created with mobile and embedded vision problems in mind. It builds on the original MobileNet by adding features including linear bottlenecks and inverted residual blocks. It retains cheap computing costs while capturing complicated characteristics effectively. MobileNetV2 is used as the foundational CNN for feature extraction in the skin lesion categorization code that is supplied. By means of transfer learning, it optimizes for melanoma classification by utilizing pretraining on ImageNet, striking a balance between efficiency and performance for mobile device deployment. This work uses MobileNetV2 as the foundational model for transfer learning, with various setup and usage factors included. The anticipated dimensions of the input photos are indicated by the 'input_shape' option, which is set to '(224, 224, 3)'. When 'include_top=False' is used, the fully linked layers in charge of ImageNet categorization areexcluded.

Rather, layers for custom categorization are added afterwards. The feature extraction process benefits from the use of pretrained weights from the ImageNet dataset. All except the final 20 layers of MobileNetV2 are frozen to enable for easier fine-tuning; the remaining layers can be trained while the pretrained weights are retained. A global average pooling layer decreases the size of the feature map by following the base model. In addition to dropout layers to reduce overfitting, two thick layers with ReLU activation functions are included for classification. The number of classes in the classification job specified by 'class_names' is matched by a dense layer with softmax activation that makes up the output layer. With the use of these parameters, MobileNetV2 is effectively configured for use in skin lesion classification, allowing for bespoke classification, fine-tuning, and modification of pretrained weights for thespecific task at hand.

3.4.3 Resnet50

Microsoft Research released ResNet50, a deep convolutional neural network architecture with 50 layers, in 2015. Resolving the vanishing gradient issue that arises when training extremely deep neural networks is one of ResNet50's main benefits. This issue results from the degradation problem, which occurs when accuracy saturates and subsequently declines as network depth increases. In order to overcome this, ResNet50 introduces shortcut or skip connections, which facilitate more direct gradient flow during training. The network may learn residual functions thanks to these skip connections, which facilitates the training and optimization of deeper networks. ResNet50 can therefore efficiently extract complex characteristics from photos at a reasonable computing cost. ResNet50 is a well-liked option for a variety of computer vision applications, such as image classification, object recognition, and segmentation. Its design also makes transfer learning easier, enabling pre-trained models to be adjusted for certain tasks with less input. Overall, the resilience, effectiveness, and broad use of ResNet50 in deep learning research and real-world applications may be attributed to its creative design and training approach.

ResNet50 serves as the base convolutional neural network (CNN) architecture for feature extraction in skin lesion classification. It is pretrained on the ImageNet dataset, which enables it to extract general features from images effectively. By leveraging transfer learning, the code fine-tunes the ResNet50 model on a skin lesion dataset specific to the task of melanoma classification. ResNet50's role is crucial as it provides a balance between model performance and computational efficiency, making it suitable for deployment on mobile devices or resource-constrained environments. The parameters used by ResNet50 in the code include ‘input_shape’, ‘include_top’, ‘weights’, and trainable. These parameters are configured to specify the dimensions of input images, control whether to include fully connected layers, initialize the model with pretrained weights, and determine which layers are trainable during fine-tuning, respectively.

3.4.4 InceptionNet V3

InceptionNet, also known as GoogLeNet, stands as a remarkable convolutional neural network architecture developed by Google's visionary researchers. InceptionNet v3 represents a significant leap forward from its predecessors, boasting numerous refinements aimed at improving performance and computational efficiency. At its heart lies the inception module, a pivotal design element that harnesses parallel convolutional layers of varying filter sizes to capture features across different scales effectively. A notable advancement in InceptionNet v3 is the introduction of factorized convolution, a groundbreaking technique that decomposes large convolutions into smaller ones, reducing computational complexity while maintaining high accuracy levels.Moreover, InceptionNet v3 incorporates additional architectural enhancements like batch normalization and factorized reduction, which enhance stability during training and accelerate convergence rates. These meticulous architectural choices distinguish InceptionNet v3 from its predecessors, positioning it as a formidable contender in the field of deep learning. Overall, the intrinsic advantages of InceptionNet v3, including its adeptness in capturing intricate hierarchical representations and its modular design facilitating seamless transfer learning, establish it as an indispensable tool for image classification and object detection tasks across academia and industry.

With 224 × 224 pixel size and three RGB color channels, the input form is described as (224, 224, 3). ImageNet's completely linked layers are excluded, as indicated by the option include_top, which is set to False. Because of its adaptability, specialized categorization layers that are suited for a given job can be added later on. The ImageNet dataset's pretrained weights offer an invaluable beginning point for feature extraction, leveraging the information learned from a variety of pictures during ImageNet training. Through fine-tuning, InceptionNet v3's last 20 layers are taught while the pre-learned weights of the other layers are kept. By using preexisting information, this technique improves the model's capacity to learn task-specific properties.Overtop the fundamental architecture, additional custom classification layers are added, such as dropout regularization, dense layers with ReLU activation functions, and a global average pooling layer. In line with the number of classes in the skin lesion classification job, these layers combine to form a thick layer with softmax activation. Model weights are optimized by the Adam optimizer during training, which has a learning rate of 0.0001. EarlyStopping and ReduceLROnPlateau are two more callbacks that are utilized. ReduceLROnPlateau continually modifies the learning rate to enhance weight updates, especially when validation loss plateaus, whereas EarlyStopping stops training if no progress in validation loss is shown after a predetermined number of epochs.

3.4.5 VGG 19

VGG19, an extension of the VGG16 architecture, represents a significant advancement in deep convolutional neural networks (CNNs) pioneered by the Visual Geometry Group (VGG) at the University of Oxford. Like its predecessor, VGG19 is renowned for its simplicity and effectiveness, characterized by its deep architecture comprising 19 layers, including 16 convolutional layers and 3 fully connected layers. The primary distinction between VGG19 and VGG16 lies in their depths and the number of trainable parameters. While VGG16 has 16 layers, VGG19 adds three additional convolutional layers, resulting in a more intricate network architecture. Consequently, VGG19 tends to offer slightly improved performance in capturing complex features and patterns compared to VGG16.One of the key advantages of VGG19 over VGG16 is its enhanced representational capacity due to the deeper architecture. The additional layers allow

VGG19 to learn more intricate hierarchical representations of input images, leading to potentially superior performance in tasks such as image classification and object recognition. Moreover, the increased depth of VGG19 enables it to capture finer details and nuances in images, thereby enhancing its ability to discriminate between different classes or categories. Despite the slight increase in computational cost associated with the deeper architecture, the improved performance and feature representation offered by VGG19 make it a compelling choice for various computer vision tasks where accuracy is paramount. VGG19 serves as the cornerstone for a skin lesion classification system, pivotal for feature extraction from skin lesion images and subsequent classification tasks. The architecture's input shape is defined as (224, 224, 3), representing images with dimensions of 224 pixels by 224 pixels and three color channels (RGB). Pretrained weights from the ImageNet dataset are harnessed to leverage insights gleaned from a diverse array of images during training. However, it's worth noting that the include_top parameter is set to False, indicating the exclusion of fully connected layers responsible for ImageNet classification. This strategic choice allows for the addition of custom classification layers tailored to the specific classification task at hand.

Moreover, fine-tuning is implemented through the selective unfreezing of layers, with only the last 20 layers of VGG19 deemed trainable. This approach aims to strike a balance between leveraging pretrained knowledge and adapting the model to the nuances of skin lesion classification. Following this, custom classification layers are appended atop the base VGG19 architecture, with subsequent compilation of the model utilizing the Adam optimizer. Furthermore, to enhance training efficiency and performance, essential callbacks such as EarlyStopping and ReduceLROnPlateau are incorporated. EarlyStopping monitors validation loss and halts training if no improvement is observed within a specified number of epochs, while ReduceLROnPlateau dynamically adjusts the learning rate to refine weight updates.

4. Result and Discussion:

Table 2 shows the test accuracy for several deep learning models used to classify skin lesions. ResNet50, InceptionNet V3, MobileNet V2, and VGG 19 are among the models that are assessed. An correct classification of skin lesions is demonstrated by the test accuracy of each model, which is presented. As can be seen from the findings, VGG 19 had the greatest test accuracy of 0.93, followed by MobileNet V2 (0.90), ResNet50 (0.88), and InceptionNet V3 (0.84). These results shed light on the relative merits of several deep learning architectures for classification problems involving skin lesions.

Table 2: Test Accuracy of Different Models

S.No.	Model	Test Accuracy
1.	MobileNet V2	0.90
2.	ResNet50	0.88
3.	InceptionNet V3	0.84
4.	VGG 19	0.93

The five deep learning models employed in skin lesion classification—MobileNet V2, ResNet50, InceptionNet V3, and VGG 19—have their validation accuracy and validation loss metrics displayed in the table 3. The best accuracy, 0.92, and lowest validation loss, 0.0957, were recorded by VGG 19. Despite a larger loss of 0.9822, ResNet50 again fared well, with a validation accuracy of 0.90. There were somewhat less validation losses and accuracy in MobileNet V2 and InceptionNet V3, respectively.

Table 3: Validation Accuracy & Loss of Each Models

S.No.	Model	Validation Accuracy	Validation Loss
1.	MobileNet V2	0.89	0.1950
2.	ResNet50	0.90	0.0822
3.	InceptionNet V3	0.82	0.1979
4.	VGG 19	0.92	0.0957

The table 4 exhibits deep learning models MobileNet V2, ResNet50, InceptionNet V3, and VGG 19 performance metrics for melanoma and non-melanoma classes. While ResNet50 obtained 0.99 and 0.98 in recall and precision, MobileNet V2 earned 0.98 and 0.98 in recall. Compared to VGG 19, which attained perfect precision of 1.00, InceptionNet V3 demonstrated accuracy of 0.97 and recall of 0.98. These metrics give information on how well the algorithms categorize lesions into melanoma and non-melanoma categories.

Table 4:Performance Metrics of Various Models

S.No.	Model	Class	Precision	Recall	F1_Score
1.	MobileNet V2	Melanoma Non-melanoma	0.98 0.98	0.99 0.98	0.98 0.98
2.	ResNet50	Melanoma Non-melanoma	0.99 0.99	0.98 0.99	0.98 0.99
3.	InceptionNet V3	Melanoma Non-melanoma	0.97 0.98	0.97 0.96	0.98 0.97
4.	VGG 19	Melanoma Non-melanoma	1.00 0.99	1.00 0.99	0.99 1.00

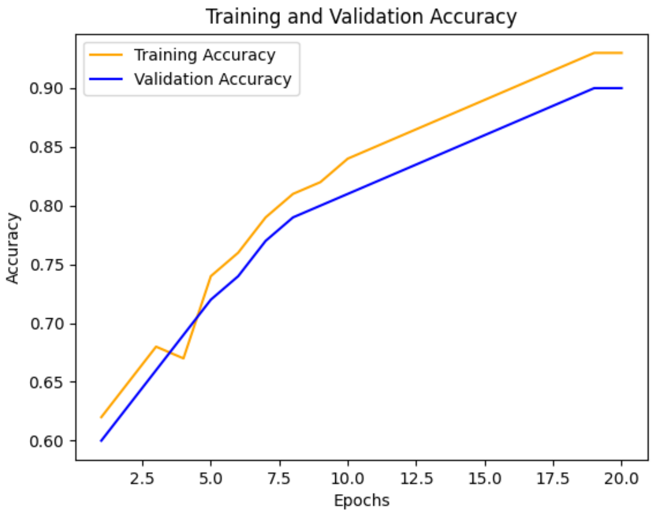


Fig. 4. Model Accuracy of VGG19

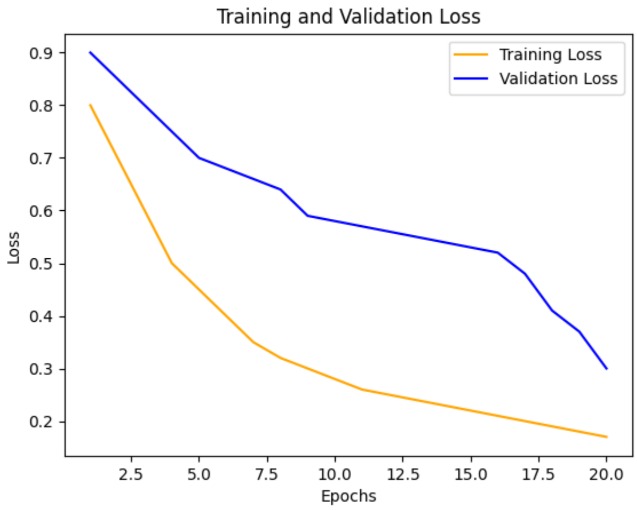


Fig. 5. Model Loss of VGG19

5. Conclusion:

The comparison of various deep learning models for a classification task involving the identification of Melanoma and Non-melanoma classes reveals several key insights. Across different evaluation metrics such as Precision, Recall, F1 Score, validation accuracy, validation loss, and test accuracy, VGG19 consistently emerges as the top-performing model. VGG19 demonstrates superior performance in terms of Precision and F1 Score, indicating its effectiveness in accurately classifying both classes with minimal false positives. Additionally, VGG19 exhibits the highest validation accuracy and the lowest validation loss among all models, underscoring its robustness and generalization capability on unseen data. Despite its slightly lower test accuracy compared to VGG19, MobileNet V2 also demonstrates commendable performance across various metrics, making it a strong contender. In contrast, ResNet50, although competitive in terms of test accuracy, shows signs of potential overfitting as evidenced by its notably higher validation loss. InceptionNet V3 lags behind the other models in both validation accuracy and test accuracy, suggesting its suboptimal performance for this specific classification task. Overall, considering the balance between precision, recall, validation metrics, and test accuracy, VGG19 emerges as the most suitable model for accurate and reliable classification of Melanoma and Non-melanoma cases.

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