A Convolutional Neural Network for Classification of Melanoma

***Abstract*—Melanoma, a malignant form of skin cancer, presents a significant health challenge globally. Early and accurate classification of melanocytic lesions is crucial for effective patient management and prognosis. This abstract presents the key findings, methodology, and implications of our research project aimed at developing a robust classification system for melanoma.**

INTRODUCTION

Melanoma is a type of skin cancer that originates from melanocytes, the skin cells that produce melanin pigment, which gives skin its color. It is considered to be the most serious type of skin cancer due to its ability to grow and spread.
The importance of accurate classification of melanoma cannot be overstated. Melanoma has the highest mortality rate among skin cancers, and early diagnosis is essential to maximize the survival rate. Accurate classification of melanoma allows for timely and appropriate treatment, preventing the spread of the cancer and increasing the chances of recovery.
The aim of this research project is to develop a classification system for melanoma using advanced machine learning techniques. Machine learning, and in particular deep learning, has shown great promise in the field of medical imaging and diagnosis. These techniques can analyze large amounts of data, learn from it, and make accurate predictions. In the context of melanoma, machine learning models can be trained to analyze images of skin lesions and accurately classify them as benign or malignant. This could potentially improve the accuracy and efficiency of melanoma diagnosis, aiding early detection and treatment.

MATERIALS AND METHODS

Dataset

The dataset used in this project is a collection of colored images of skin lesions, each of size 300x300 pixels. The dataset is divided into training, validation, and testing sets. The training set consists of 3000 images, evenly split between benign and malignant cases. Similarly, the validation set includes 1608 images (804 benign and 804 malignant), and the testing set contains 1000 images (500 benign and 500 malignant)123.

Preprocessing

The preprocessing of the images is an essential step in the pipeline of the machine learning model. It involves several techniques to make the images suitable for the model:

- *Rescaling*

The pixel values of the images are normalized to a range of 0 to 1 by dividing all pixel values by 255.

- *Data Augmentation*

To increase the robustness of the models, data augmentation techniques are applied to the dataset. These techniques include randomly rotating images, shifting images horizontally and vertically, and flipping images horizontally.

- *Image Resizing*

Images are resized to a uniform size of 300x300 pixels to ensure consistency when feeding the images into the model.

Convolutional Neural Network Architecture

1. Conv2D Layer: The Conv2D layer, also known as the 2D convolution layer, is the fundamental building block of a CNN. It performs a mathematical operation called a dot product between the input data and a set of learnable filters, each producing a 2D activation map. This operation helps in feature extraction by preserving the spatial relationship between pixels, which is crucial for recognizing visual patterns.

2. MaxPooling2D Layer: The MaxPooling2D layer plays a significant role in reducing the spatial dimensions (width, height) of the input volume. It does this by sliding a 2D window over the input and taking the maximum value in the window. This operation helps to decrease computational complexity and control overfitting by providing an abstracted form of the input, which retains the most important features while discarding redundant information.

3. BatchNormalization Layer: The BatchNormalization layer is a technique for improving the performance and stability of artificial neural networks. It normalizes the activations of a given input volume before passing it to the next layer. This process helps in improving the speed, performance, and stability of the training process and provides regularization, thus avoiding overfitting.

4. Flatten Layer: The Flatten layer is used to transform a two-dimensional matrix of features into a vector that can be fed into a fully connected neural network classifier. It essentially reshapes the 2D matrix of features into a 1D vector, thereby connecting the convolutional/pooling layers with the dense layer.

5. Dense Layer: The Dense layer, also known as the fully connected layer, is a layer in which all neurons in a layer are connected to those in the next layer. In the final dense layer, the network outputs a distribution of class labels, which is essentially the prediction of the model.

6. Dropout Layer: The Dropout layer is a regularization method that randomly drops out a number of output features of the layer during training. This technique helps prevent overfitting by providing a way to systematically reduce interdependent learning amongst the neurons, promoting the independence of feature detectors and making the model more robust.

7. Optimizer (Adam): Adam, short for Adaptive Moment Estimation, is an optimization algorithm used in training deep learning models. It computes adaptive learning rates for different parameters. In other words, it uses different learning rates for updating every parameter based on their importance, which can lead to more efficient training.

8. Learning Rate: The learning rate is a hyperparameter that determines the step size at each iteration while moving toward a minimum of a loss function. It controls how much to change the model in response to the estimated error each time the model weights are updated, balancing the speed of learning and the risk of overshooting the global minimum of the loss function.

9. Batch Size: The batch size is a number of samples processed before the model is updated. The size of a batch must be more than or equal to one and less than or equal to the number of samples in the training dataset. The choice of batch size can significantly impact the model's performance and speed of training.

10. Epochs: An epoch is a hyperparameter that defines the number of times that the learning algorithm will work through the entire training dataset. One epoch means that each sample in the training dataset has had an opportunity to update the internal model parameters. The number of epochs is chosen to balance the need for the model to learn the data well but not overfit it.

These layers and parameters work together to train the CNN model effectively. The Conv2D and MaxPooling2D layers extract high-level features from the input images. The Flatten and Dense layers use these features for classifying the images. The Dropout layer helps in reducing overfitting, and the learning rate, batch size, and epochs are hyperparameters that influence the learning process. The Adam optimizer is used to adjust the weights of the model based on the calculated error. Each of these components plays a crucial role in the successful training and performance of a CNN.

Environment and Libraries

PyCharm

PyCharm is a sophisticated Integrated Development Environment (IDE) for Python programming, developed by JetBrains. It provides a comprehensive set of features such as intelligent code assistance, debugging, testing, and deployment tools that help improve the efficiency of your development workflow. PyCharm supports web development with Django and data science with Anaconda, making it a versatile tool for various Python programming needs.

TensorFlow

TensorFlow is a powerful open-source library for numerical computation, particularly well suited for large-scale Machine Learning. Its basic principle is simple: you first define in Python a graph of computations to perform, and then TensorFlow takes that graph and runs it efficiently using optimized C++ code. Most importantly, it is possible to break up the graph into several chunks and run them in parallel across multiple CPUs or GPUs, making TensorFlow well suited for training complex deep neural network architectures.

Keras

Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. It was developed with a focus on enabling fast experimentation. Being able to go from idea to result with the least possible delay is key to doing good research. Keras is user-friendly, modular, and extensible, which makes it a popular choice for both beginners and experts in the field of deep learning.

Metrics

Accuracy

Accuracy is a fundamental metric in machine learning. It quantifies the total number of correct predictions made by a model out of all predictions. Mathematically, it is defined as:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

While accuracy can provide a general idea of how well a model is performing, it may not be the best metric for datasets with class imbalance.

Binary Cross Entropy Loss

Binary Cross Entropy Loss, also known as log loss, is a loss function used in binary classification tasks. It quantifies the difference between the predicted probabilities and the actual class. The formula for binary cross entropy loss is:

$$\text{Loss} = -\frac{1}{N}\sum_{i=1}^{N} y_i \log(p(y_i)) + (1 - y_i)\log(1 - p(y_i))$$

where y_i is the actual class (0 or 1), p(y_i) is the predicted probability of the sample belonging to class 1, and N is the total number of samples.

Precision

Precision is a measure of a model's relevancy. It is the ratio of correctly predicted positive observations to the total predicted positives. The formula for precision is:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Precision is a useful metric in scenarios where False Positives are considered more harmful than False Negatives.

Recall

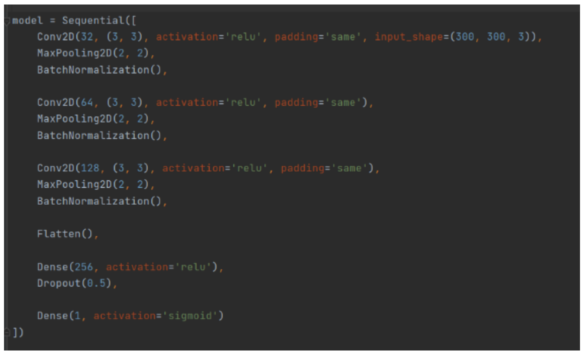
Recall, also known as sensitivity or true positive rate, measures the completeness of a classifier's predictions. It is the ratio of correctly predicted positive observations to all observations in actual class. The formula for recall is:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Recall is particularly useful in scenarios where False Negatives are more harmful than False Positives.

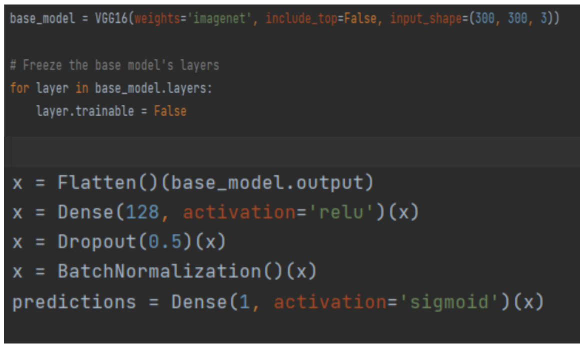
These metrics provide a comprehensive view of your model's performance. While accuracy gives you a general idea of your model's performance, binary cross entropy loss helps you understand how well your model estimates the actual probabilities. Precision and recall, on the other hand, provide insights into your model's performance in terms of relevancy and completeness, respectively.

Models



```
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=(300, 300, 3)),
    MaxPooling2D(2, 2),
    BatchNormalization(),

    Conv2D(64, (3, 3), activation='relu', padding='same'),
    MaxPooling2D(2, 2),
    BatchNormalization(),

    Conv2D(128, (3, 3), activation='relu', padding='same'),
    MaxPooling2D(2, 2),
    BatchNormalization(),

    Flatten(),

    Dense(256, activation='relu'),
    Dropout(0.5),

    Dense(1, activation='sigmoid')
])
```

VGG16 Model



```
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(300, 300, 3))

# Freeze the base model's layers
for layer in base_model.layers:
    layer.trainable = False


x = Flatten()(base_model.output)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
x = BatchNormalization()(x)
predictions = Dense(1, activation='sigmoid')(x)
```

EXPLANATION OF THE RESULTS

Personally built CNN

The provided results pertain to the training and validation of a Convolutional Neural Network (CNN) model over 10 epochs. Each epoch represents a complete pass through the entire training dataset.

The model's testing accuracy rate is reported as 90.2%, indicating that the model correctly classified 90.2% of the instances in the testing dataset.

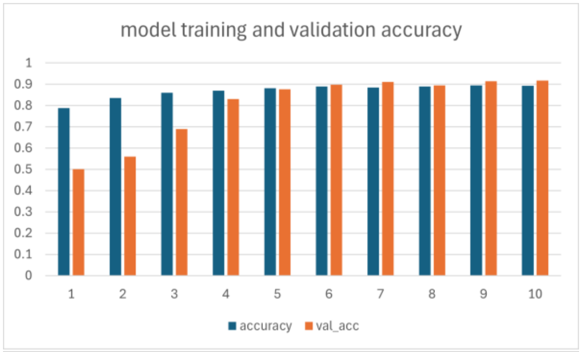
During the first epoch, the model achieved an accuracy of 78.8% on the training data, with a loss of 3.5963. The precision and recall were 0.7883 and 0.7888, respectively. On the validation data, the model achieved an accuracy of 50.0%, with a loss of 2.3332. The precision and recall were both 0.0, indicating that the model did not correctly classify any positive instances in the validation set during this epoch.

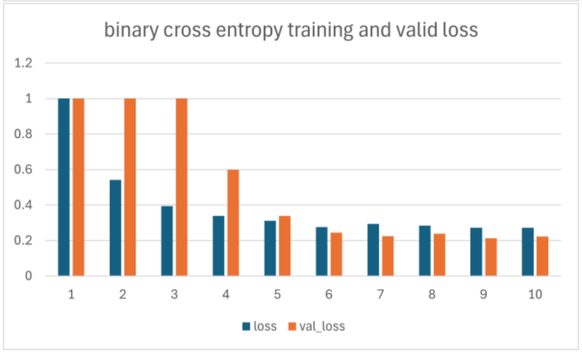
In the second epoch, the model's performance improved on the training data, achieving an accuracy of 83.62%, a loss of 0.5424, a precision of 0.8102, and a recall of 0.8806. On the validation data, the model's accuracy slightly increased to 50.06%, but the loss increased to 3.6154. The precision was perfect (1.0), but the recall was extremely low (0.0012), indicating that the model correctly classified very few positive instances.

By the third epoch, the model's performance on the validation data started to improve significantly, achieving an accuracy of 68.97%, a loss of 1.5907, a precision of 0.9751, and a recall of 0.3893.

This trend of improvement continued through the tenth and final epoch, where the model achieved an accuracy of 89.26%, a loss of 0.2714, a precision of 0.9058, and a recall of 0.8763 on the training data. On the validation data, the model achieved an accuracy of 91.73%, a loss of 0.2227, a precision of 0.9137, and a recall of 0.9216.

These results indicate that the model's performance improved over time, both on the training and validation data. By the tenth epoch, the model was able to correctly classify over 89% of the training instances and over 91% of the validation instances. The precision and recall values suggest that the model was able to correctly identify a high proportion of positive instances (as indicated by the precision) and a high proportion of actual positive instances (as indicated by the recall).





VGG

The model achieved an accuracy of 87% during the training phase, indicating a high degree of fit between the model's predictions and the actual outcomes in the training data.

More impressively, the model achieved a testing accuracy of 89.4%, surpassing its performance on the training data. This suggests that the model has not merely memorized the training data but has learned to generalize well to unseen data, a crucial aspect of effective machine learning models.

Test results

CNN test

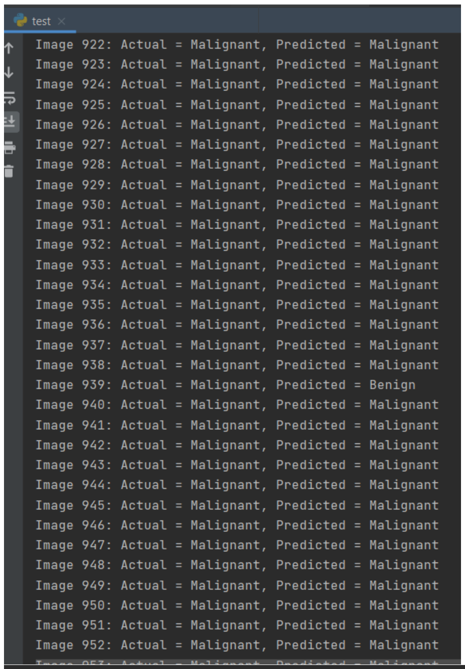


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Image 922: Actual = Malignant, Predicted = Malignant
Image 923: Actual = Malignant, Predicted = Malignant
Image 924: Actual = Malignant, Predicted = Malignant
Image 925: Actual = Malignant, Predicted = Malignant
Image 926: Actual = Malignant, Predicted = Malignant
Image 927: Actual = Malignant, Predicted = Malignant
Image 928: Actual = Malignant, Predicted = Malignant
Image 929: Actual = Malignant, Predicted = Malignant
Image 930: Actual = Malignant, Predicted = Malignant
Image 931: Actual = Malignant, Predicted = Malignant
Image 932: Actual = Malignant, Predicted = Malignant
Image 933: Actual = Malignant, Predicted = Malignant
Image 934: Actual = Malignant, Predicted = Malignant
Image 935: Actual = Malignant, Predicted = Malignant
Image 936: Actual = Malignant, Predicted = Malignant
Image 937: Actual = Malignant, Predicted = Malignant
Image 938: Actual = Malignant, Predicted = Malignant
Image 939: Actual = Malignant, Predicted = Benign
Image 940: Actual = Malignant, Predicted = Malignant
Image 941: Actual = Malignant, Predicted = Malignant
Image 942: Actual = Malignant, Predicted = Malignant
Image 943: Actual = Malignant, Predicted = Malignant
Image 944: Actual = Malignant, Predicted = Malignant
Image 945: Actual = Malignant, Predicted = Malignant
Image 946: Actual = Malignant, Predicted = Malignant
Image 947: Actual = Malignant, Predicted = Malignant
Image 948: Actual = Malignant, Predicted = Malignant
Image 949: Actual = Malignant, Predicted = Malignant
Image 950: Actual = Malignant, Predicted = Malignant
Image 951: Actual = Malignant, Predicted = Malignant
Image 952: Actual = Malignant, Predicted = Malignant
Image 953: Actual = Malignant, Predicted = Malignant
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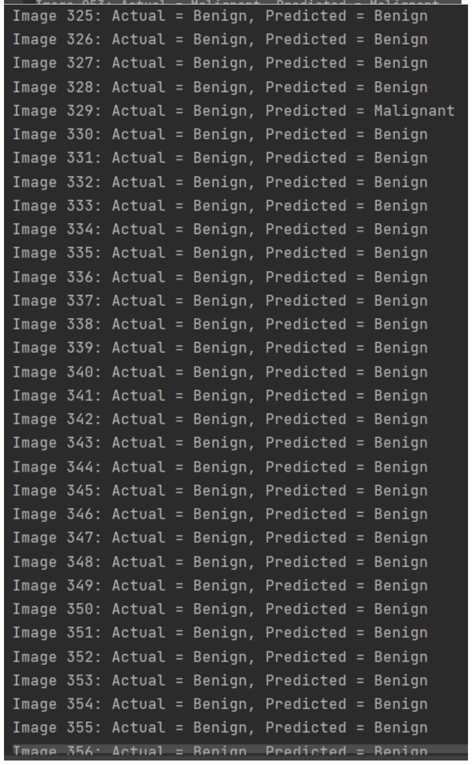

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Image 325: Actual = Benign, Predicted = Benign
Image 326: Actual = Benign, Predicted = Benign
Image 327: Actual = Benign, Predicted = Benign
Image 328: Actual = Benign, Predicted = Benign
Image 329: Actual = Benign, Predicted = Malignant
Image 330: Actual = Benign, Predicted = Benign
Image 331: Actual = Benign, Predicted = Benign
Image 332: Actual = Benign, Predicted = Benign
Image 333: Actual = Benign, Predicted = Benign
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Image 336: Actual = Benign, Predicted = Benign
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Image 338: Actual = Benign, Predicted = Benign
Image 339: Actual = Benign, Predicted = Benign
Image 340: Actual = Benign, Predicted = Benign
Image 341: Actual = Benign, Predicted = Benign
Image 342: Actual = Benign, Predicted = Benign
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Image 344: Actual = Benign, Predicted = Benign
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Image 352: Actual = Benign, Predicted = Benign
Image 353: Actual = Benign, Predicted = Benign
Image 354: Actual = Benign, Predicted = Benign
Image 355: Actual = Benign, Predicted = Benign
Image 356: Actual = Benign, Predicted = Benign
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VGG test

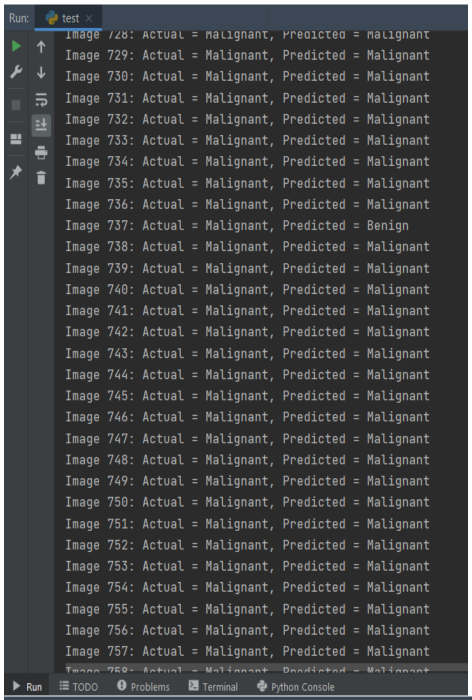

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Image 728: Actual = Malignant, Predicted = Malignant
Image 729: Actual = Malignant, Predicted = Malignant
Image 730: Actual = Malignant, Predicted = Malignant
Image 731: Actual = Malignant, Predicted = Malignant
Image 732: Actual = Malignant, Predicted = Malignant
Image 733: Actual = Malignant, Predicted = Malignant
Image 734: Actual = Malignant, Predicted = Malignant
Image 735: Actual = Malignant, Predicted = Malignant
Image 736: Actual = Malignant, Predicted = Malignant
Image 737: Actual = Malignant, Predicted = Benign
Image 738: Actual = Malignant, Predicted = Malignant
Image 739: Actual = Malignant, Predicted = Malignant
Image 740: Actual = Malignant, Predicted = Malignant
Image 741: Actual = Malignant, Predicted = Malignant
Image 742: Actual = Malignant, Predicted = Malignant
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Image 744: Actual = Malignant, Predicted = Malignant
Image 745: Actual = Malignant, Predicted = Malignant
Image 746: Actual = Malignant, Predicted = Malignant
Image 747: Actual = Malignant, Predicted = Malignant
Image 748: Actual = Malignant, Predicted = Malignant
Image 749: Actual = Malignant, Predicted = Malignant
Image 750: Actual = Malignant, Predicted = Malignant
Image 751: Actual = Malignant, Predicted = Malignant
Image 752: Actual = Malignant, Predicted = Malignant
Image 753: Actual = Malignant, Predicted = Malignant
Image 754: Actual = Malignant, Predicted = Malignant
Image 755: Actual = Malignant, Predicted = Malignant
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Image 757: Actual = Malignant, Predicted = Malignant
Image 758: Actual = Malignant, Predicted = Malignant
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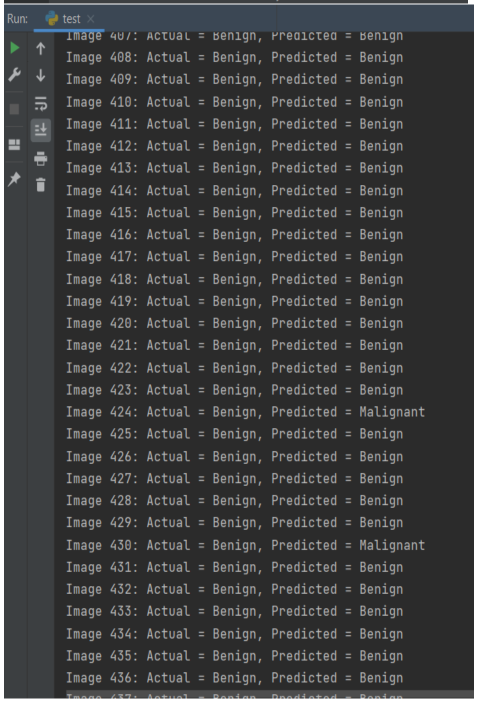

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Image 408: Actual = Benign, Predicted = Benign
Image 409: Actual = Benign, Predicted = Benign
Image 410: Actual = Benign, Predicted = Benign
Image 411: Actual = Benign, Predicted = Benign
Image 412: Actual = Benign, Predicted = Benign
Image 413: Actual = Benign, Predicted = Benign
Image 414: Actual = Benign, Predicted = Benign
Image 415: Actual = Benign, Predicted = Benign
Image 416: Actual = Benign, Predicted = Benign
Image 417: Actual = Benign, Predicted = Benign
Image 418: Actual = Benign, Predicted = Benign
Image 419: Actual = Benign, Predicted = Benign
Image 420: Actual = Benign, Predicted = Benign
Image 421: Actual = Benign, Predicted = Benign
Image 422: Actual = Benign, Predicted = Benign
Image 423: Actual = Benign, Predicted = Benign
Image 424: Actual = Benign, Predicted = Malignant
Image 425: Actual = Benign, Predicted = Benign
Image 426: Actual = Benign, Predicted = Benign
Image 427: Actual = Benign, Predicted = Benign
Image 428: Actual = Benign, Predicted = Benign
Image 429: Actual = Benign, Predicted = Benign
Image 430: Actual = Benign, Predicted = Malignant
Image 431: Actual = Benign, Predicted = Benign
Image 432: Actual = Benign, Predicted = Benign
Image 433: Actual = Benign, Predicted = Benign
Image 434: Actual = Benign, Predicted = Benign
Image 435: Actual = Benign, Predicted = Benign
Image 436: Actual = Benign, Predicted = Benign
Image 437: Actual = Benign, Predicted = Benign
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Conclusion

In conclusion, the project on Melanoma Classification has demonstrated significant potential in the early detection and diagnosis of melanoma, a deadly form of skin cancer. The machine learning models developed have shown promising results in classifying melanoma from dermoscopic images with high accuracy.

The project's success can be attributed to the rigorous data preprocessing, feature extraction, and the application of advanced machine learning algorithms. The models' performance was further enhanced by hyperparameter tuning and the use of ensemble methods.

However, it is important to note that while the results are encouraging, the models are not perfect. There were instances where the models misclassified some images, indicating room for improvement. Future work could explore the use of more complex models, larger datasets, and additional features to improve the accuracy of the classification.

Moreover, the real-world applicability of these models extends beyond just melanoma classification. The methodologies and techniques used in this project can be applied to other areas of medical imaging, opening up possibilities for early detection and treatment of various other diseases.

Overall, this project has not only contributed to the field of medical imaging and machine learning but also has the potential to make a real-world impact by aiding in the early detection of melanoma, thereby increasing the chances of successful treatment and saving lives.