12-2023

MELANOMA DETECTION BASED ON DEEP LEARNING NETWORKS

Sanjay Devaraneni

MELANOMA DETECTION BASED ON DEEP LEARNING NETWORKS

A Project

Presented to the

Faculty of

California State University,

San Bernardino

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

In

Computer Science

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by

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Approved by:

Dr. Qingquan Sun, Advisor, Computer Science and Engineering

Dr. Jennifer Jin, Committee Member

Dr. Yan Zhang, Committee Member

ABSTRACT

Our main objective is to develop a method for identifying melanoma enabling accurate assessments of patient's health. Skin cancer, such as melanoma can be extremely dangerous if not detected and treated early. Detecting skin cancer accurately and promptly can greatly increase the chances of survival. To achieve this, it is important to develop a computer-aided diagnostic support system.

In this study a research team introduces a sophisticated transfer learning model that utilizes Resnet50 to classify melanoma. Transfer learning is a machine learning technique that takes advantage of trained models for similar tasks resulting in time saving and enhanced accuracy by avoiding the need to train from scratch.

The Resnet50 is a type of network that can distinguish between cancerous skin lesions in each sample. To evaluate its performance, we used data from the melanoma cancer dataset. However, the dataset has a percentage of samples which creates an imbalance between the classes. We addressed this issue by making the dataset more diverse through data augmentation techniques.

In our project we implemented the Resnet50 pretrained model with learning rates and weight decay. This model consists of 50 layers organized into blocks that include batch normalization and skip connections (known as connections). We adjusted the depth of the model to improve its accuracy.

Our experimental results demonstrate that our proposed deep learning technique performs better in terms of accuracy compared to state of the art algorithms in this field.

The model achieves an accuracy of 91.70%, with a learning rate of 0.0001 and a model depth of 34. By tuning hyperparameters using RESNET 50 we can further enhance the accuracy of our trained models.

ACKNOWLEDGEMENTS

I would like to take this moment to express my gratitude for the support I have received throughout this research journey. It is because of each member of my committee, their guidance, and their belief in me that we have achieved such an outcome. Dr. Qingquan Sun, I am incredibly grateful for your feedback at every stage of the project. Your input has been tremendously beneficial. Has growth in numerous ways. To Dr. Jennifer Jin and Dr. Yan Zhang I extend my thanks for agreeing to be part of my committee. Your trust has been an inspiration to me, always pushing me towards excellence as we navigated through each step of the process together. Lastly, I would like to acknowledge all the professors at the University who have played a role in shaping my path; your efforts in providing us students with the highest quality education are deeply appreciated.

I want to express my appreciation to the School of Computer Science, at California State University San Bernardino for creating a curriculum that perfectly matches my goals and aspirations.

My journey through school would have felt incomplete if I didn't hold onto the words that were spoken to me a long time ago. Our education is something that will always belong to us, and no one can ever take it away. These words resonated with me as I reached this milestone; it required strength, determination, and unwavering dedication to achieve my goals.

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CHAPTER ONE

INTRODUCTION

Background

Melanoma, a dangerous kind of skin cancer, is caused by melanocytes, the epidermal cells responsible for creating the melanin pigment. This type of tumor is the most common cause of death although making up a small portion of all cutaneous malignancies. It is well known in the literature that early melanoma diagnosis is still challenging. For those who are at high risk of developing the disease in the first place and who have melanoma, early identification is essential for increasing survival chances. Most of the time, a dermatologist will identify melanoma by a preliminary visual inspection, typically using polarized light magnified dermoscopy.

The goal is to employ computer vision, machine learning, and deep learning to extract information from digital images and generate new knowledge. To distinguish between images of melanoma and non- melanoma, deep neural networks are used in dermatology. Early detection of melanoma is crucial because it increases the chance of a successful cure, especially in people who are at high risk of getting the disease.

Significance

Technology has the potential to significantly affect the way we think about medicine. It is also a key element of contemporary diagnostic tools that support our ability to make decisions that are crucial to patient care. Comparing clinical photos with and without segmentation will help you determine how well melanoma is classified. There are various concepts for computer-aided dermatological systems presently available, however despite claims that AI can perform many tasks better than doctors, there are still many challenges to be solved.

Most of the features of this software are based on computer vision-related techniques, such as border recognition, symmetry/asymmetry analysis, color analysis, and dimension detection. There may be a need to return to the lab, train the model once more, test it once more, and deploy it once more if a new image dataset is produced that is more precise and polished.

Motivation

Detecting melanoma using deep learning models is driven by the desire to achieve precise, effective, and timely identification of skin cancer. Melanoma, the form of skin cancer can be life threatening if not detected and treated early on.

Deep learning models have exhibited immense potential in diverse medical contexts. Deep learning models have shown remarkable abilities in recognizing and classifying images. By utilizing extensive collections of dermoscopic images, these models can achieve great precision in differentiating harmless moles from potentially cancerous melanomas.

As a result, they effectively minimize the occurrences of both false negatives and false positives. Detecting melanomas early is extremely important as it leads to better patient outcomes and more successful treatment.

Deep learning algorithms can play a significant role in identifying melanomas during their early stages, making them easier to manage and increasing the likelihood of successful treatment. This not only has the potential to save lives but also reduces the necessity for invasive interventions.

CHAPTER TWO

LITERATURE SURVEY

Over the years there have been advancements in the field of skin cancer detection using image analysis. Many different techniques have been explored. The International Skin Imaging Collaboration (ISIC) [1] event has gained recognition as a respected benchmark for skin cancer detection featuring a challenge contest. In addition to that there have been reports of applications being developed to aid in skin cancer detection. Researchers have been dedicated to improving accuracy by employing classification algorithms and techniques.

Image classification has reached heights with the introduction of neural network (CNN) structures pioneered by Fukushima and later Le-Cunn [2]. These CNNs imitate the visual cognition system. Are regarded as the most advanced methods for image classification. While there is an abundance of literature, on image classification this review specifically focuses on learning methods applied to skin cancer images.

Esteva et al. [3] made progress in the field of skin cancer classification. Their study focused on utilizing networks, specifically a CNN model to analyze an extensive collection of images showcasing various skin lesions, including cases of melanoma. By training the model with an architecture they successfully developed an algorithm of identifying and categorizing different types of skin cancer. The results were truly remarkable, with the system achieving accuracy levels to those of dermatologists in detecting melanoma and other skin lesions. This study holds promise for improving detection of skin cancer, particularly melanoma thereby leading to better treatment outcomes, for patients.

Convolutional networks, with capabilities (FCNs) can efficiently infer and learn from inputs of sizes producing corresponding outputs of the same size. Detecting melanoma accurately is vital to lower the mortality rate associated with this disease at its stages. To identify melanoma a two-step approach is employed. This includes separating skin lesions and recognizing melanoma lesions. The accuracy of segmentation is improved by incorporating two FCNs based on VGG 16 and Google Net into a framework.

For classification purposes features are extracted from lesions using both a residual network and a hand-crafted feature. The classification process utilizes support vector machine. Our framework demonstrates promising accuracy in performance analysis, achieving a classification score of 0.8892 for the ISBI 2016 dataset and 0.853, for the ISIC 2017 Dataset.

Prassanna et al [4] developed an approach that leverages machine learning to identify and classify skin lesions. They designed a network that successfully recognizes the boundaries of lesions. To improve the precision of predictions they also built a phone model by applying transfer learning and tuning techniques to the deep neural Network.

Panja et al. [5] conducted a study where they differentiated between melanoma and benign skin cancer. They utilized a CNN model to extract features from skin cells by segmenting skin images. Another research concentrated on categorizing photos from the ISIC 2019 Dataset into eight groups. The researchers trained their model by employing Resnet 50 and fine tuning the parameter values, through transfer learning. Any images that do not belong to these eight categories are labeled as unknown.

In tackling the Melanoma detection issue, for this project we make use of the Resnet 50 model. Apply a transfer learning technique based on research. To guarantee the accuracy of our model we carefully adjust the hyperparameters in a manner.

CHAPTER THREE

SYSTEM ARCHITECTURE

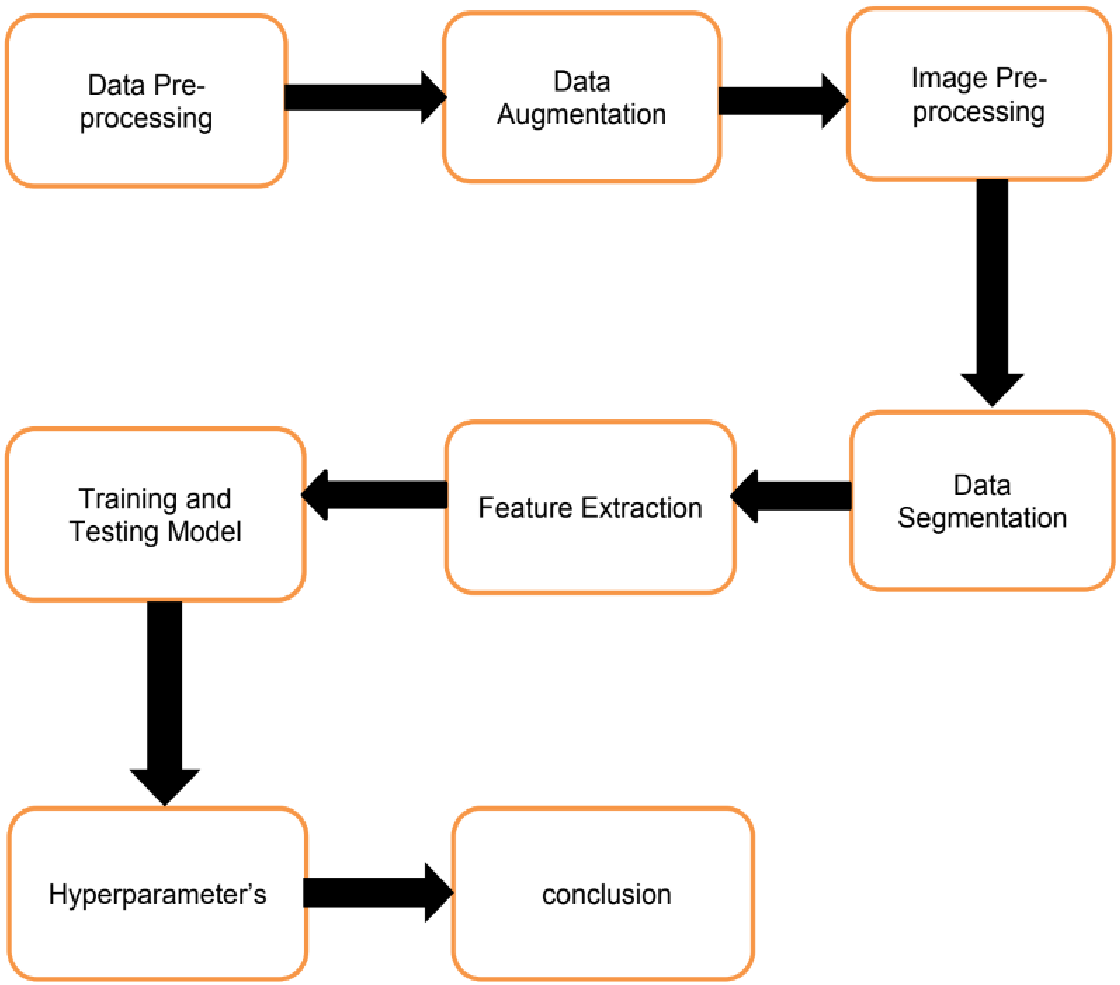


Figure 1. The sequential pipeline for Melanoma Detection

Data Pre-Processing

In Figure 1 the first step, in the pipeline, for Melanoma Detection is Data pre-processing. To start you'll need to gather a collection of skin lesion images for your dataset. This dataset should include both melanoma and non-images and can be obtained from various sources like public repositories or healthcare facilities. It's crucial to ensure that the dataset is properly labeled, distinguishing between melanoma and non-images. Once you have the dataset, you'll need to load it into your programming environment. The dataset may come in formats such as CSV, JSON or image files like JPEG or PNG. If the data is in image format you might need to use libraries like OpenCV or PIL to read and make any adjustments. If the data is structured (CSV or JSON) tools like Pandas can be used for loading it.

For image analysis results it’s recommended to normalize values within a standardized scale (0 to 1). To tackle the difficulties of interpreting imaging data that involves factors, like melanoma, we have undertaken a project focused on adjusting the pixel ranges of all graphics to a scale of 0 255 values. To reduce noise, we employ Gaussian blur filters, which have proven to be more effective than methods such as median filtration. Additionally, we normalize the graphics by cropping them to a standard size scale.

Data Augmentation

Data augmentation is a technique, in machine learning and computer vision where the training dataset is expanded by increasing its size and diversity through various transformations or alterations. In the context of diagnosis data augmentation can involve making changes to images of skin lesions to provide additional training samples. Deep learning models often apply data augmentation by making modifications to the existing data or generating data points. Some used methods for augmenting melanoma detection datasets include rotation, flipping, scaling, translation, zooming, noise addition and cropping. In Figure 2, the original image is Augmented into new images with different methods. Interestingly deep neural networks are not affected by changes like fading or flipping images vertically or horizontally at angles.

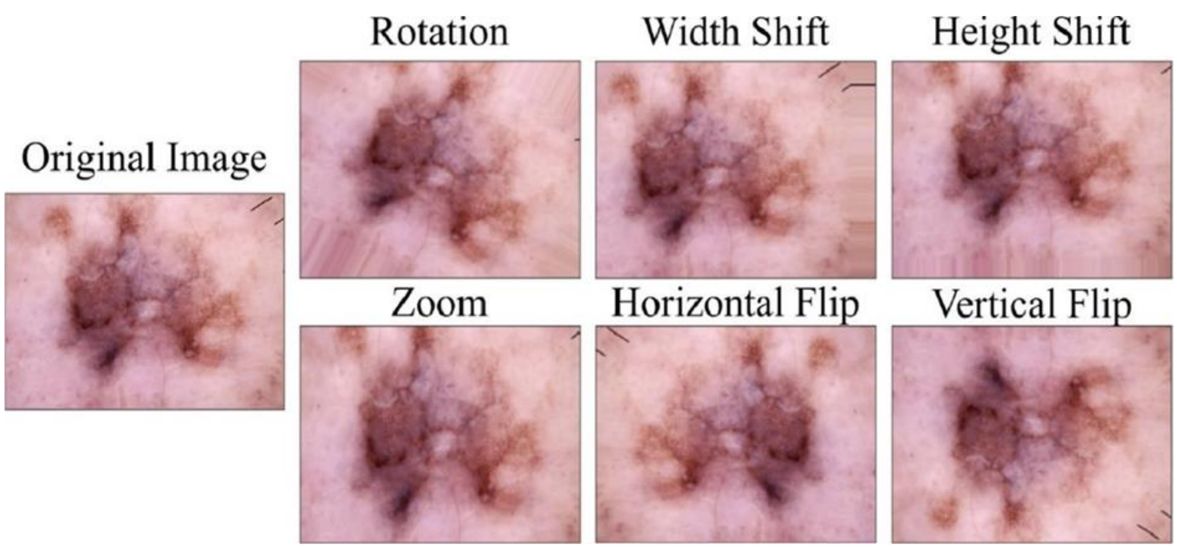


Figure 2. Augmented Images of Skin Lesion

Image Pre-Processing

In the field of dermatology one of the tasks is to detect melanoma accurately. To improve the accuracy of this process image preprocessing plays a role. In dermatology the outcomes of the processing step can be categorized into three main groups: image enhancement, image restoration and hair removal. In Figure 3, the hair is removed from the original image through image Pre-processing. For analysis it is essential to resize all images to the dimensions through image rescaling. This helps in normalizing the data and ensuring that all images have a resolution. To enhance the quality of images various techniques can be employed. Sometimes images may contain noise due to factors like acquisition artifacts or insufficient lighting conditions.

By applying denoising methods such as Gaussian filtering we can reduce noise to improve image quality. Additionally, techniques like segmentation or thresholding can be used to separate and extract skin lesions or areas that are in question. However, it should be noted that specific preprocessing methods may vary depending on factors such as characteristics, imaging equipment used, and specifications of the melanoma detection algorithm being employed. Furthermore, researchers are currently studying a method based on filtering to remove hair from skin images. One way to improve melanoma detection is by converting the image from the RGB color space to a color space like CIELAB or HSV. These alternative representations may be more suitable for the task.

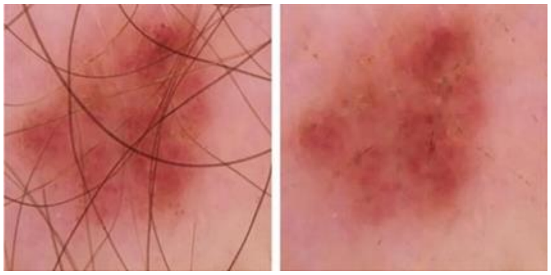


Figure 3. Image Pre-Processing

Data Segmentation

Detecting melanoma involves a step known as data segmentation. This step entails separating or isolating regions, such as skin lesions or suspicious areas from the rest of an image. Thresholding is an easily executed technique that uses a threshold value to create a binary mask on an image. It is crucial to take into account the qualities and features of each image when deciding on an image processing method. Depending on these factors' different types of thresholding methods, such as adaptive or Ousts thresholding methods may be employed. To identify regions within images region-based techniques have been developed, with one popular approach being the use of the region growing algorithm. With this method a seed point is used to group neighboring pixels that meet criteria like color and texture similarity. One advantage of this technique is its ability to accurately generate lesion regions. Edge detection techniques aim to determine boundaries that separate areas within an image.

In the case of detecting melanoma lesions methods, like edge detection or gradient based approaches can be applied to identify edges. These identified edges can then be effectively used to outline the region caused by the lesion. When it comes to understanding medical imaging data it's worth exploring machine learning techniques. For instance, convolutional neural networks (CNNs) have shown promise in segmenting regions of interest within images.

The basic idea behind this approach involves teaching CNN what constitutes these regions by using labeled datasets with pixel level annotations. To effectively capture the shape and boundaries of a region of interest super pixel-based techniques are utilized. These techniques group pixels with attributes into super pixels. It's important to note that popular methods like SLIC and Watershed segmentation can be helpful in generating these images. Once these images are generated researchers can employ them for evaluations.

Feature Extraction

The detection and classification of melanoma can be supported by analyzing images of skin lesions to look for any signs that may indicate this illness. It is crucial to optimize the identification of these markers through feature extraction. Extracting features from images plays a role in efficient recognition and diagnosis for melanoma patients. One approach to detect melanoma is by analyzing the colors on human skin lesions.

A method called color-based feature extraction' can be used for this purpose. By converting an images format into color spaces like RGB or HSV we can obtain specific statistical measurements such as mean values or histogram-based statistics, which are necessary to identify any noticeable changes within the target area. It's worth noting that melanoma lesions often exhibit texture patterns. Research has shown that it is possible to extract characteristics using methods such as binary patterns (LBP) gray level co-occurrence matrix (GLCM) or Gabor filters.

In Figure 4, feature extraction has been done on images by applying border and color to the images. These characteristics encompass measurements such as entropy smoothness of the root mean square, skewness, symmetry, kurtosis mean texture variance, centroid, central tendency inverse difference moment correlation energy contrast shade eccentricity. It is worth noting that the selection of techniques to extract these features relies on factors like the dataset itself, image quality, computational resources, at hand and the effectiveness of the chosen algorithm or classifier.

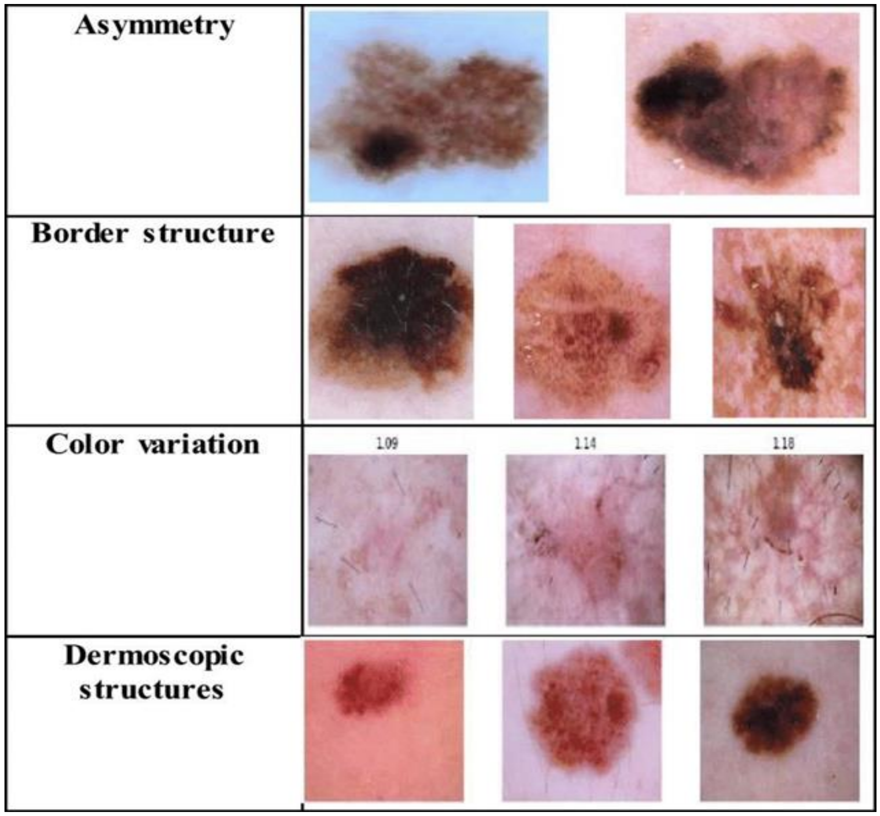


Figure 4. Feature Extraction Images of Skin Lesion

Training and Testing

To ensure the performance accuracy of your model it is necessary to divide the dataset into two categories; a training set and a testing/validation set. The training set helps in preparing the model while the testing/validation set determines how well it performs in producing results. Before embarking on this journey, it is crucial to train your chosen AI model by using a carefully curated training dataset. The main goal is for your machine learning architecture to gradually understand how different patterns or attributes distinguish between melanoma and non-skin abnormalities. To evaluate the effectiveness of a trained model it is essential to test it with the testing/validation set.

The model's performance can then be assessed by measuring metrics such as accuracy, precision, recall and F1 score. To gain insights into its predictions compared to expected outcomes we can generate a confusion matrix that provides information about positive/negative as well as false positive/negative predictions. Achieving optimal performance levels, with the model requires an approach that includes tuning and experimenting with hyperparameters like learning rates and regularization techniques. It is also important to explore architecture for improvements.

To start our project, we need to divide the dataset into segments. We will allocate 80% of the data for training, 10% for testing and another 10% for validation purposes. The reason we chose to use ResNet50 as a component in our training model is because it plays a role in our framework. We will train this model using the allocated datasets. Then adjust the accompanying parameters as needed. After completing this process, we will move on to testing the model using a test dataset.

CHAPTER FOUR

DEEP LEARNING

Deep learning is a part of machine learning that focuses on the decision making and accurate prediction capabilities of networks. It draws inspiration from the structure and functioning of the brain particularly how individual neurons are interconnected within a network. Deep learning algorithms aim to learn and extract features from amounts of data. They are called "deep" because they rely on layers of neurons that form neural networks often with millions or even billions of connections, between them.

The scientific process of learning involves training a network using a labeled dataset that contains known correct outputs or labels. The network adjusts its parameters, such as weights and biases, to minimize errors between its predictions and the actual data. One key advantage of learning is its ability to automatically acquire features from raw information without requiring explicit input, for feature engineering. It has achieved results in fields, including speech recognition and computer vision, continuously raising the bar for performance standards.

Convolutional Neural Networks (CNNs) are commonly employed in the field of computer vision to perform tasks such as image classification and object detection. On the hand Recurrent Neural Networks (RNNs) have demonstrated promise, in handling data especially for language modeling and speech recognition purposes. However recently Transformer models with self-attention mechanisms have gained attention due to their ability to excel in machine translation and text generation tasks.

Deep learning has truly revolutionized industries, including healthcare, finance, autonomous vehicles, and entertainment. Its real-world applications encompass areas such as diagnosis, fraud detection, recommendation systems, autonomous driving and even the creation of realistic videos and images. While deep learning models offer benefits it is important to note that they require computational resources for effective training.

For tasks related to image classification and face identification experts often prefer using networks (CNNs). CNNs are highly effective in analyzing complex forms of data thanks to their advanced technology capabilities. One key reason for their effectiveness is their three structures, which allows them to extract important features from images and categorize them accordingly. At the core of a CNN architecture lies the convolutional layer. In this setup we have a Single Layer CNN architecture along with layers that are part of it.

The initial layer, known as the input layer, receives values from an input image and processes them. Following that is the layer in the network configuration. Its objective is to capture and retain aspects from data samples while preserving crucial connections between pixels. In this stage of processing various functions such as smoothening, sharpening or detecting edges in images are performed by applying filters to images. Within the network model there exists a layer known as the activation layer. Its purpose is to calculate an output based on input values that have been weighted.

After that we come across a layer known as pooling which plays a role in simplifying the intricacy of images with varying sizes by decreasing the number of involved parameters. Spatial pooling can be accomplished through techniques like max pooling, which selects elements, average pooling, which calculates the average value of all components, in a feature map and sum pooling, which adds up all identified elements. In the layer the output matrix obtained from the pooling layer is transformed into a vector through fully connected layers. One notable strength of CNN models is their accuracy achieved by utilizing training data, with minimal image preprocessing requirements.

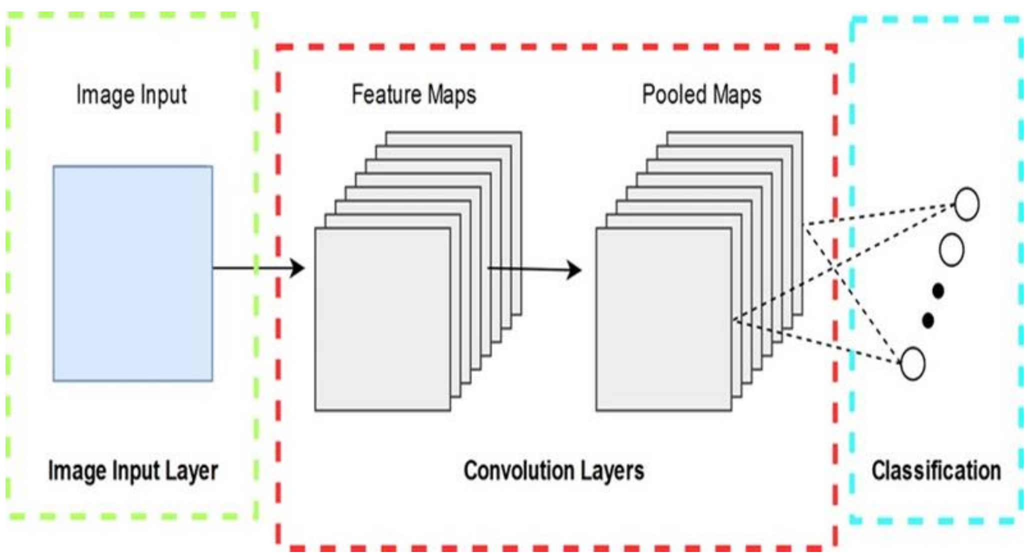


Figure 5. Single Layer Convolutional Neural Network

Transfer Learning

Transfer learning is an essential concept in the deep learning field. This widely used technique facilitates the application of previously acquired knowledge from one model onto another related task. Pre-existing models that have already undergone significant training with big datasets are now adjusted to cater to smaller but related datasets. Transfer learning allows us to leverage the knowledge stored in a trained model instead of starting from scratch with a new model. This approach saves resources. Eliminates the need for a large amount of labeled data.

Transfer learning presents various benefits, with its greatest advantages being the ability to apply pre-trained models that can solve related tasks quicker and more accurately. Reduced training time, Improved generalization, Efficient with tiny datasets.

Resnet-50

The Resnet50 model is a type of Convolutional Neural Network that consists of 50 layers. Out of these 50 layers 48 are specifically designed for performing Convolutional operations. Additionally, the model incorporates one max pool layer and one intermediate pool layer. The first version of Resnet was called Resnet 34 which had a total of 34 layers. In this model all the convolutional networks used filters of size 3*3. Were influenced by the VGG neural network, particularly VGG 16 and VGG 19.

The architectural design of Resnet50 can be visualized through Figure 11. With the four distinct blocks labelled as follows: stem block (a), Stage-1 Block represented twice with blocks (b) and (c), along with a fully connected counterpart known as block(d). As for its basic framework, the Resnet50 abides by two fundamental principles of design. Firstly, it's important to mention that all layers have filters regardless of the size of the output feature map. Secondly when the feature map size is reduced by half, we include many filters to preserve the temporal complexity of each layer.

A popular choice for computer vision tasks like image classification, object detection, and image segmentation is the ResNet-50 architecture. This model's depth and skip connections have proven useful for mitigating the vanishing gradient problem. This capability allows for the creation of deeper models with greater accuracy than standard architecture could provide. In this project, we made changes to Hyperparameters like the learning rate and weight decay values.

The Resnet architecture follows a structure called building blocks, which are usually composed of blocks. Each residual block consists of layers and shortcuts that allow us to adjust the depth of the network as needed. By modifying the number of blocks or layers in a ResNet architecture, such as ResNet 50 we can customize its depth. In our case we decided to make the model less deep by removing some blocks from ResNet 50 resulting in a model called ResNet 34. This adjustment was made with the intention of enhancing the accuracy of our model.

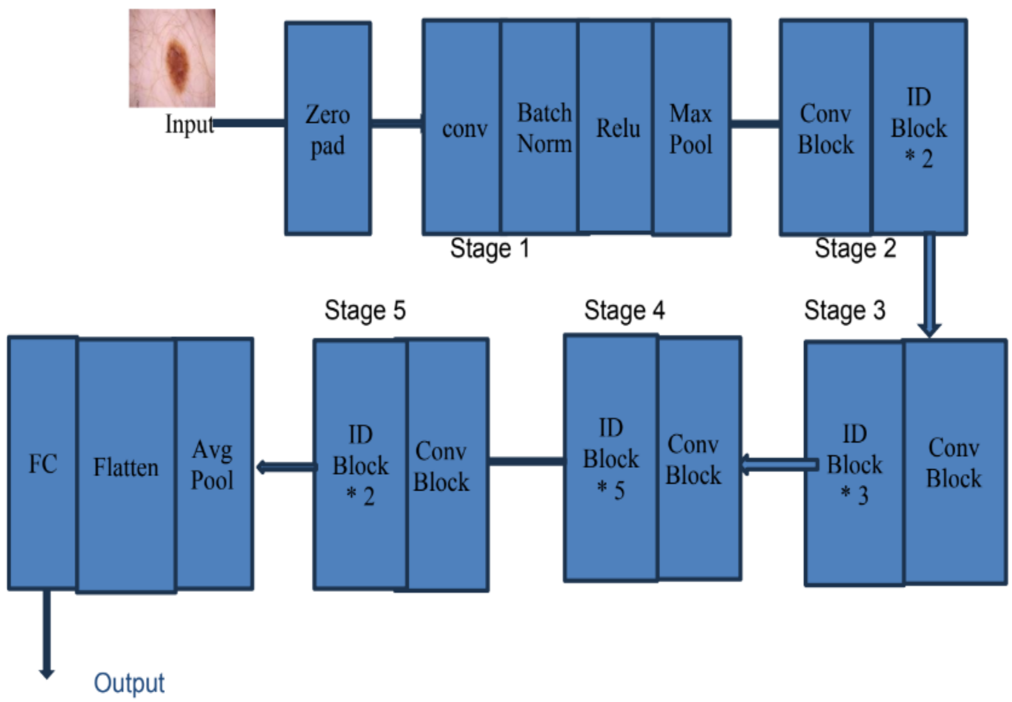


Figure 6. Resnet50 Architecture

CHAPTER FIVE

EXPERIMENTAL SETUP

Dataset

To approach our melanoma detection problem, we accessed a dataset available on Kaggle consisting of almost 10000 images with melanoma. Ensuring that our results would be meaningful required us to slice the data into suitable training and testing sets while following certain conditions. Notably, we made sure that our chosen test set did not differ in traits from our training set and that the dataset itself was sufficiently large enough to lend informative conclusions drawn from it. These decisions were supported by previous research papers provided as references throughout this process. In conclusion, our data was divided into three separate segments - with a majority (80%) allocated towards training alongside two evidently smaller subsets (10%) each reserved for validation and testing purposes.

Hardware Requirements

- Memory: 4 GB RAM (minimum)

- Hard drive: at least 250GB
- CPU: Intel Core i5 or above
- OS: Linux, Windows, Mac OS.

Software Requirements

Jupyter

Jupyter is a web application that anyone can use to create and share documents. It allows users to combine code equations, visuals, and informative text in one place. It’s a handy tool. Jupyter predominantly utilizes notebooks as their file format where they can be comprised of an array of interesting cells- textbased or visualizations or even codes. The exceptional part is that users possess the ability to both write and execute codes specifically within individual notebook cells with instantaneous results neatly displayed within the same document. This characteristic establishes a firm foundation for its aptitude to cater towards demanding technical facets like scientific computing, machine learning which significantly accelerate computational tasks.

Python:

The Python programming language is extensively used and offers users a plethora of benefits, such as platform independence, flexibility, a vast community support system, and an extensive library collection. For this project, the libraries utilized consist of NumPy, TensorFlow, cv2, Keras, PyTorch, plotly, shutil, itertools, imutils and matplotlib.

Evaluation Metrics

The accuracy score is determined by calculating the proportion of predicted data samples out of the number of input samples.

Accuracy = TP+TN/TP+TN+FP+FN

The ratio of accurate positive predictions to all predicted positives is known as precision. This value can be indicative of how often false positives occur - with higher precision typically being associated with fewer errors in this regard.

Precision = TP/TP+FP

The ratio of accurately predicted positive samples to all samples in the actual class is what determines the result.

Recall = TP/TP+FN

Its definition is that it is the Harmonic Mean between recall and precision. Therefore, this score accounts for both false positives and false negatives.

F1 = 2 * (Precision * Recall/Precision + Recall)

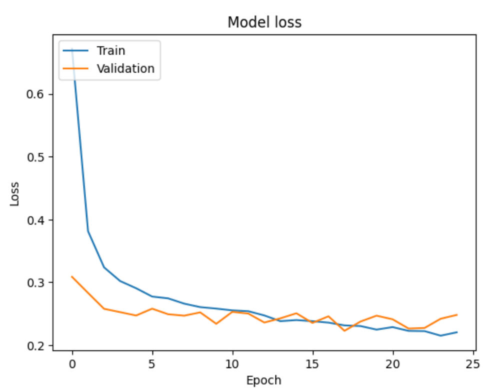
CHAPTER SIX

EXPERIMENTAL RESULTS

Hyperparameter Tuning Analysis

Experiment 1: Learning Rate: 0.0001

In this study we use the ResNet50 algorithm to train the model for classifying skin cancer. To ensure optimization we set the learning rate at 0.0001, which determines how big of a step is taken in each iteration. It's important to note that using a learning rate may lead to convergence but may also prevent us from reaching the ideal solution.



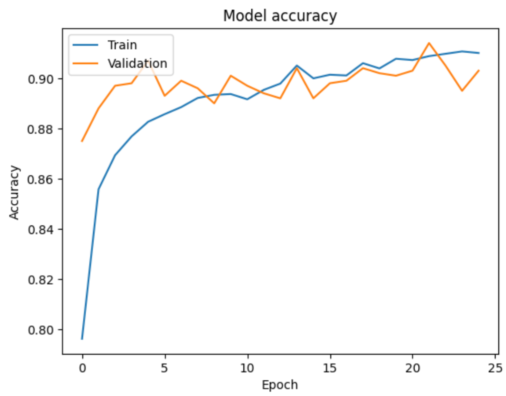


Figure 7. Training and Validation Accuracy of Experiment 1

Experiment 2: Learning Rate: 0.01

To build upon our research we proceeded with experiments utilizing the ResNet50 algorithm just as we did before. However, this time we made an improvement by adjusting our learning rate value to 0.01. Our objective is to investigate how these minor tweaks can positively influence the efficiency and accuracy of our model. It's worth noting that increasing the learning rate value may result in a decrease in accuracy.

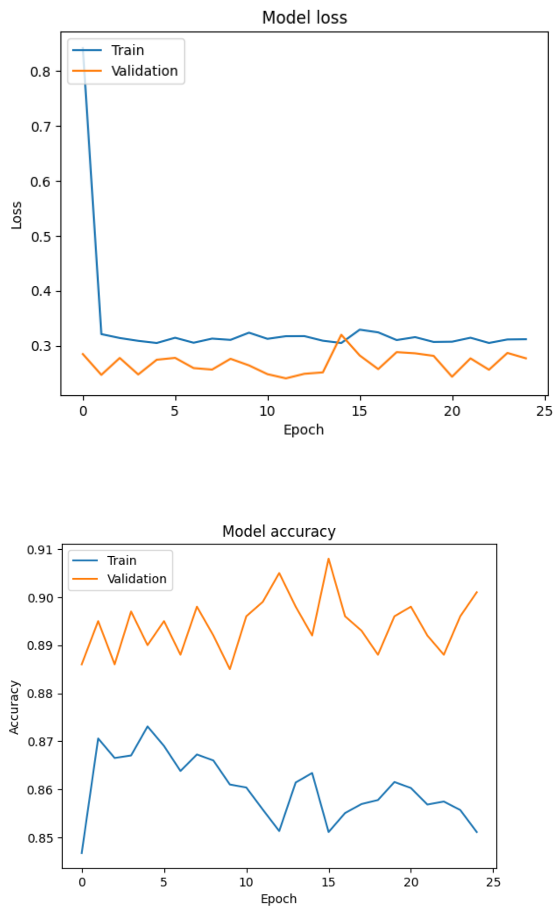


Figure 8: Training and Validation Accuracy of Experiment 2

Experiment 3: Learning Rate: 0.5

To investigate the impact of a learning rate, on the model's performance this experiment incorporates an increased learning rate of 0.5 resulting in larger optimization steps. It is worth noting that while the decay value remains constant at 1e 2 a higher learning rate could lead to a decrease in accuracy, to 50%.

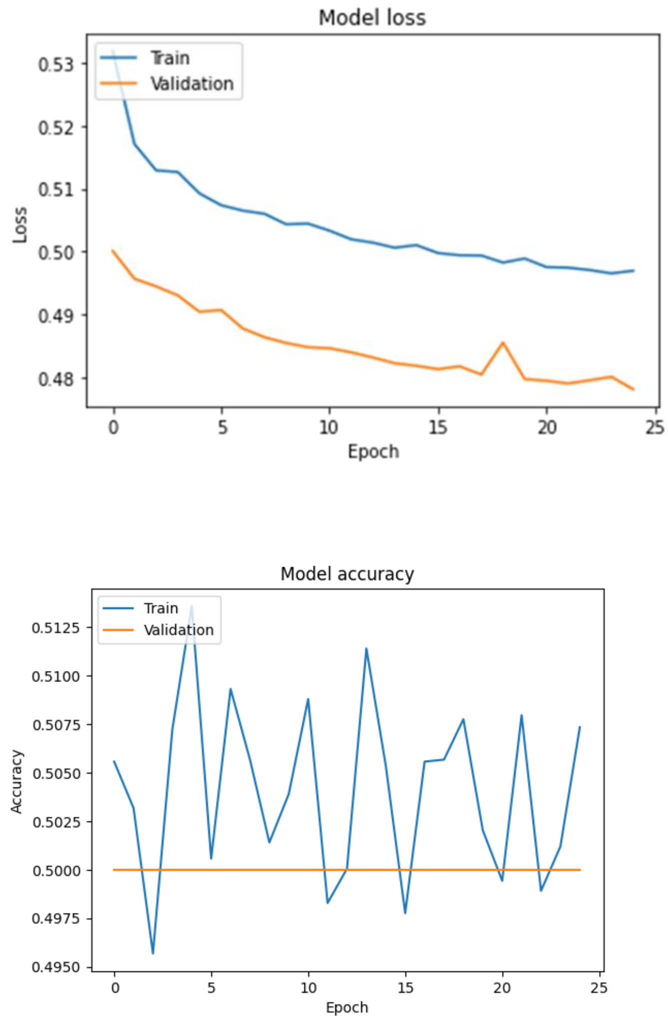
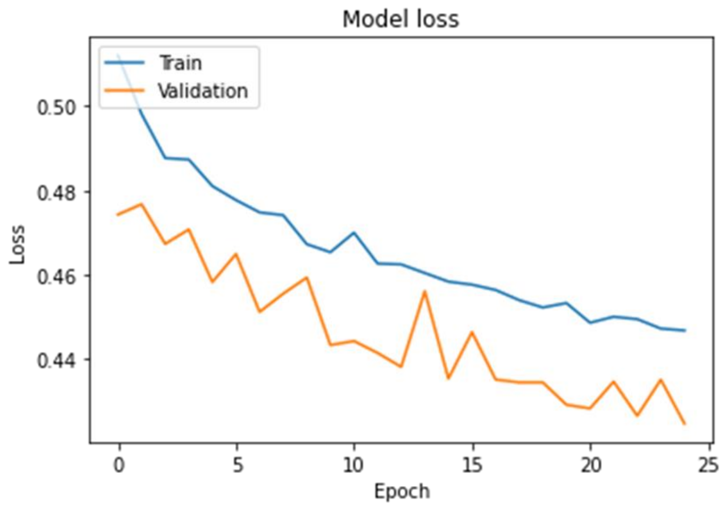


Figure 9. Training and Validation Accuracy of Experiment 3

Experiment 4: Learning Rate: 0.1

The learning rate has been adjusted to 0.1. The weight decay value is set at 0.004 resulting in an increase in accuracy. During the analysis there was an improvement in accuracy compared to the previous experiment.



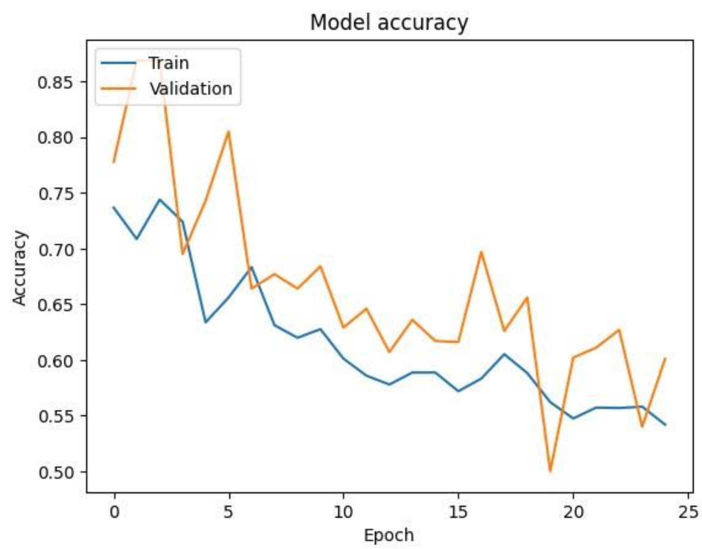


Figure 10: Training and Validation Accuracy of Experiment 4

<u>Experiment 5: Learning Rate: 0.09</u>

We are currently running an experiment using a learning rate of 0.09 which exceeds the level we tried before. Throughout this trial the decay value remains at 0.003. Our objective is to investigate whether the performance of the models is affected by a learning rate. It's important to note that accuracy might decline when the learning rate is set high as it depends on factors such as the dataset and system model. Hyperparameters can also have an impact on accuracy.

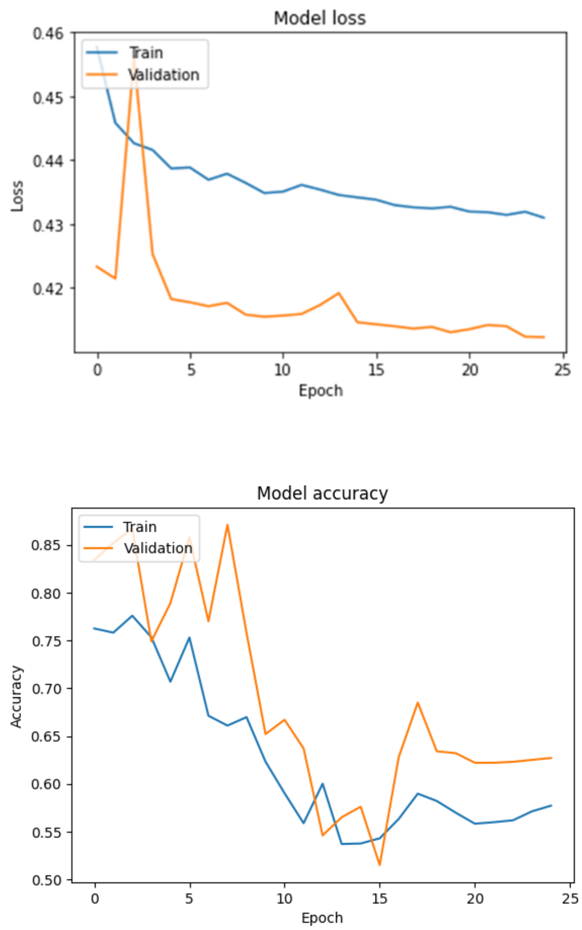
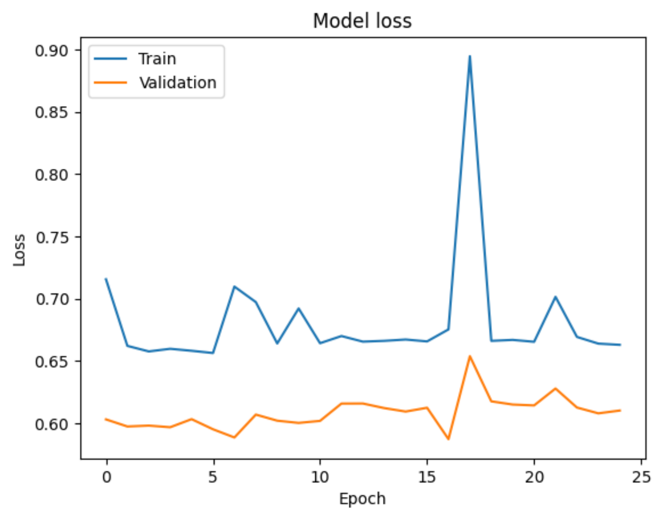


Figure 11. Training and Validation Accuracy of Experiment 5

Experiment 6: Learning Rate: 0.05

To examine the effects of a decay value when combined with a learning rate we will conduct an experiment where the decay value is reduced to 1e 2 for evaluation purposes.



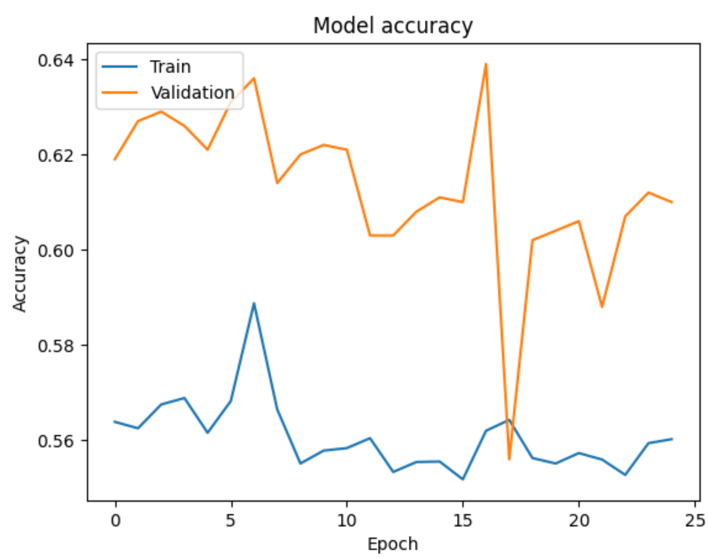
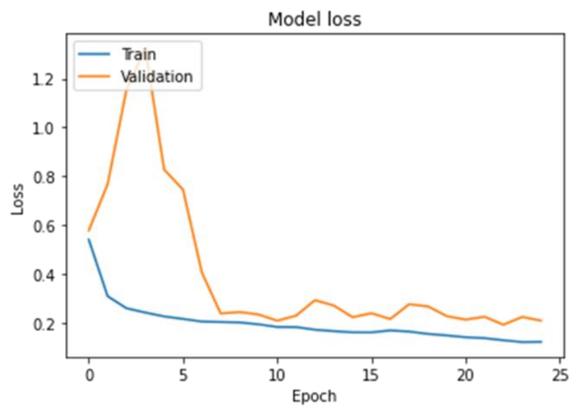


Figure 12: Training and Validation Accuracy of Experiment 6

Experiment 7: Learning Rate: 0.001, Depth: 34

It introduces some modifications to the ResNet50 architecture aiming to investigate its performance in the classification of skin cancer. The model's depth has been reduced to 34 resulting in layers while its width has been expanded to 64 layers. When the learning rate is set at 0.001 and the decay value at 0.0004, we observe a level of accuracy. By adjusting hyperparameters such as depth and width we can enhance accuracy levels.



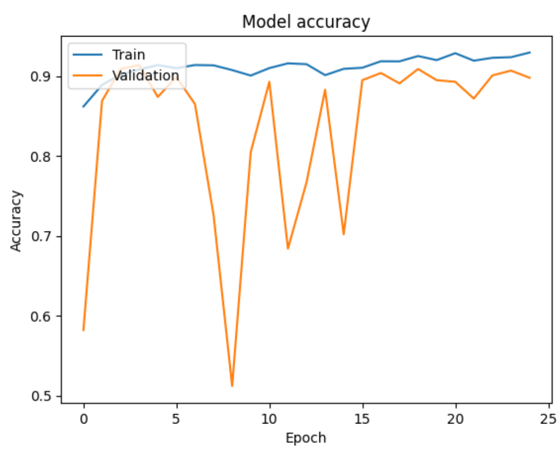
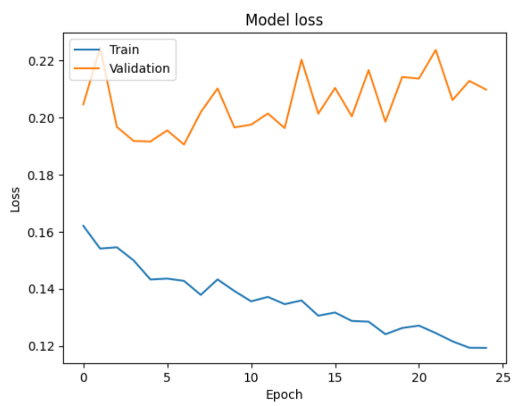


Figure 13. Training and Validation Accuracy of Experiment 7

Experiment 8: Learning Rate: 0.0001, Depth: 34

The value of the learning rate is set at 0.0001. We achieved 90% accuracy. To improve the accuracy of the model we made modifications to the Resnet 50 Architecture by removing the blocks. The model has a depth of 34 and a width of 64. When the learning rate is set at 0.0001 and the decay value at 0.000004, we observe a level of accuracy. We can further enhance accuracy levels by adjusting hyperparameters like depth and width.



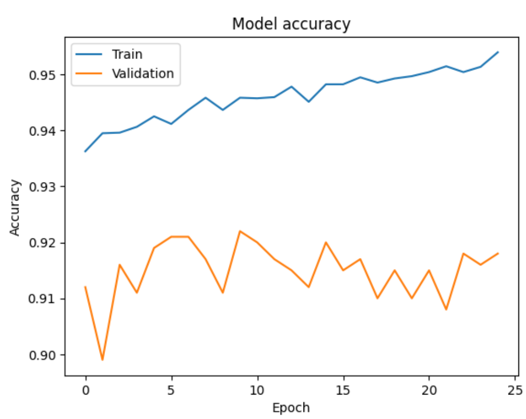


Figure 14: Training and Validation Accuracy of Experiment 8

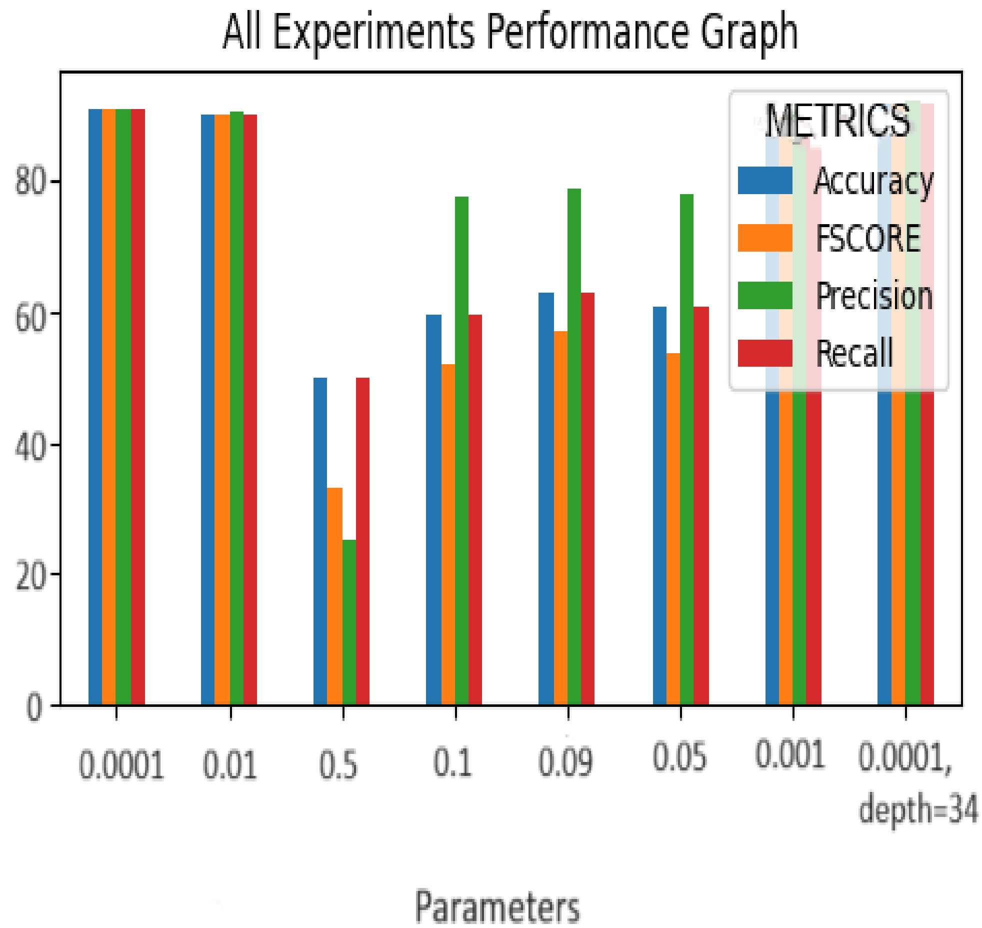


Figure 15. Comparison Graphs

Table 1. Comparison of The Hyperparameters with Resnet50 Model

Learning Rate	Accuracy	Precision	Recall	F Score
0.0001	90.80	90.92	90.80	90.79
0.01	90.00	90.28	89.99	89.98
0.5	50.00	25.00	50.00	33.33
0.1	59.69	77.68	59.69	51.88
0.09	62.80	78.66	62.80	56.82
0.05	60.80	78.02	60.80	53.68
0.001, depth=34	91.20	91.55	91.19	91.18
0.0001, depth=34	91.70	92.07	91.70	91.68

CHAPTER SEVEN

CONCLUSION

While melanoma may be considered one of the worst types of skin cancer due to its high mortality rate when left untreated long enough, there's hope if you receive an early-stage diagnosis. This form of cancer can become much less threatening with timely identification and subsequent intervention. One important component in achieving this desirable outcome involves utilizing proven diagnostic technologies that aid physicians in detecting malignant growths sooner rather than later.

These imaging modalities derive from specific evaluations formulated by experts who specialize in identifying signs of melanoma while they are still confined solely within local lymph nodes. In our research we present a transfer learning approach that utilizes Resnet50 to identify melanoma and benign skin lesions.

This method can be applied to examine any concerning skin lesion. We have tested the approach on a Melanoma dataset containing images of skin-cancer disorder to distinguish between benign and malignant diseases. To bolster the size of the dataset and enhance Resnet50's accuracy, data augmentation techniques were employed. With a diagnostic accuracy of 91.70 percent, this technique proves to be effective. Additionally, it's worthwhile to compare this approach with others prevalent in the field. The suggested architecture outperforms many state-of the-art models without requiring model training from scratch to enhance model efficiency. In due course, this study will be conducted on skin cancer images of Pakistani patients once there is an adequate collection of high-resolution photographs.

According to our findings, CNN networks performed better when not divided. Moreover, the study revealed that the skin surrounding wounds can provide crucial information that should be considered during training. Therefore, we recommend conducting further research while evaluating alternative pre-processing methods.

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