AN APPROACH TO DETECT MELANOMA SKIN CANCER USING FASTAI CNN MODELS

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **An approach to Detect melanoma skin cancer Using fastai CNN Models**, submitted by Md Shazzad Mia and Sumaiya Mustari Mim to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 25/01/2023.

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We hereby declare that, this project has been done by us under the supervision of **Mohammad Jahangir Alam, Lecturer, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Skin cancer, which can be lethal, is essentially the improper proliferation of skin tissues. It has recently developed into one of the most dangerous sorts of additional malignancies in humans. Early detection may help the patient endure. Skin cancer is notoriously difficult to detect. Currently, computer vision performs incredibly well when used to diagnose medical images. Along with technological development and the rapid rise in computer accessibility, several machine learning algorithms and deep learning algorithms have been developed for the interpretation of medical images, especially images of skin lesions. According to our paper, there are five fast-ai CNN pretrained models with various image pre-processing techniques that enhance the classification capability of skin lesions and make them more precise than other existing models. The HAM10000 dataset's benign and malignant cancer lesions are distinguished by utilizing a number of pre-processing methods. The experimental findings showed that the suggested model improved its accuracy to 97% in both training and testing.

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CHAPTER 1

Introduction

1.1 Introduction

One of the deadliest types of skin cancer is melanoma. 75% of skin cancer-related deaths globally are due to melanoma. Because it affects the melanocyte cells, melanoma restricts the production of melanin [1]. Early melanoma detection is therefore essential in the fight against cancer-related deaths. Only early-stage detection of the disease can reduce the mortality rate because skin cancer is one of the most treatable malignancies [2]. According to the Skin Cancer Foundation, over two individuals in the US die from skin cancer every hour, and over 9500 new cases are documented. According to the European Cancer Information System, there will be 2.7 million new cases of cancer and 1.3 million cancer-related deaths in 2020. In 2020, people over 65 accounted for 62% of new diagnoses and 76% of mortality, it was discovered. The importance of early skin cancer identification and diagnosis has been shown in previous studies. An in-depth study has recently focused on the creation of computer image analysis algorithms, and deep learning technology is currently considerably assisting in the way of early skin cancer identification. In order to build the fast-AI CNN technique for classifying images of skin lesions, we pre-trained many models to provide superior results with a high classification rate [3].

1.2 Motivation

The majority of individuals in our country are unaware of skin problems. Furthermore, they do not believe that consulting a doctor about the ailment in its early stages is vital. So developing an easy approach to diagnosing this condition would be extremely beneficial. Melanoma is a dangerous type of skin cancer. It's more dangerous because if it's not treated early, it can spread to other organs more quickly. In fact, only 20–30% of melanoma is detected in existing moles, while 70–80% is found in normal skin. Other skin illnesses, such as acne, are also harmful, but melanoma is the most lethal. And identifying these disorders is difficult. That is why we are focusing on seven different types of skin problems.

1.3 Rationale of the study

Melanoma is a type of cancer that begins in the melanocytes. These are the cells that produce the skin pigment known as melanin. Melanin protects the deeper layers of the skin from the damaging effects of the sun. Sunlight stimulates your skin to produce more melanin, which causes it to darken. Melanoma cancer cells can still produce melanin. This is why these malignancies may appear in a variety of colors, such as tan, brown, blue, or black. Melanoma can spread to other parts of the body if it is not detected and treated early. Melanoma cells that have spread to key organs are difficult to treat and are unlikely to be cured. Melanoma can develop on the skin without any warning. It could also start inside or around a mole or other dark patch on the skin. That's why it's critical to know the color, size, and position of the moles on your body so you can spot any changes.

1.4 Research Questions

Many different questions about this study could be asked in various ways. A series of questions were obtained from multiple people to make this study more compact.

Why do we use CNN for image analysis?

Convolutional neural networks are a type of neural network that is mostly employed in image and speech recognition applications. Its integrated convolutional layer decreases image dimensionality without sacrificing information. As a result, CNNs are ideal for this application.

What is the main advantage of CNN?

The fundamental advantage of CNN over its predecessors is that it automatically discovers significant features without the need for human intervention. For example, given a large number of images of cats and dogs, it learns distinguishing features for each class on its own.

1.5 Expected Output

Our research will make it easier for people to diagnose diseases in their early stages. We are working hard to improve the correctness of our project. Our fast-AI CNN model will correctly detect the diseases. People will submit photographs of their skin, and our technology will identify the specific disorders.

1.6 Report Layout

This research report is broken into six distinct sections to make it more understandable and beneficial for readers and researchers.

Chapter 1 served as an important introduction to this study project. This brief information refers to the likelihood of surviving tonsil cancer. This chapter discusses the research motivation, the rationale for this study, pertinent research questions, expected results, overall management information, and financial difficulties. The context of this investigation is explained in detail in

Chapter 2. For instance, consider the categorization data from this research study, as well as the machine learning approaches and associated studies. This chapter discusses comparative analysis as well as the scope of this issue statement's predicted obstacles.

Chapter 3 is a full description of the methodology. This chapter offers information about the structure of this research endeavor.

Chapter 4 provides a full examination of each stage of the outcomes. This chapter also illustrates each result from the experiments.

Chapter 5 discusses the implications of this research for society, the environment, and long-term sustainability.

Chapter 6 depicts the future scope of this scientific activity. The full research report is concluded in this chapter, with a relevant conclusion that briefly highlights the key findings of this study.

CHAPTER 2
Background

2.1 Preliminaries

The majority of our time was spent processing data. Cropping and resizing the image, as well as the data in train and valid 80/20. In addition, we employ a ranger optimizer to apply discriminative learning, fit one cycle to implement transfer learning and fine-tune to use transfer learning.

2.2 Related Works

According to Salian, Abhishek C., et al., their study's [4] innovative CNN model generated a testing accuracy of 80.61%. By utilizing a different deep CNN model, they may increase their categorization rate. An image processing tool and computer-aided model are used to track melanoma skin lesions, and the results of the suggested technique are often acceptable. The program's ability to automatically diagnose skin cancer is enabled by its improved usability and conciseness for acquired pictures [5]. According to a study [6], both supervised and unsupervised classification can be used to identify skin cancer using certain machine learning algorithms. SVM, neural networks, and K-means clustering are a few examples. However, if more data were used, the accuracy might be improved.[7] states that the authors developed a DCNN, trained it, and then utilized it to categorize skin lesions in a resource-constrained mobile-ready DNN architecture using images from multiple thermoscope libraries.48,373 thermoscope images were used, which were collected from three archives, categorized, and verified by dermatologists with training. They also developed a thorough mobile base classifier for identifying lesions. This outcome, however, might have been improved if the DNN model's confidence spectrum, which was dependent on classification accuracy, had been used.

An approach for early skin cancer diagnosis using SVM algorithms and the Gray Level Co-occurrence Matrix was proposed by Ansari, Uzma Bano, et al. [8] and showed encouraging outcomes. However, they might have improved their outcome by utilizing a number of helpful tactics. In [9], the authors used a histogram of an Oriented Gradient operator to depict skin lesions. Stagnation is alleviated using local binary patterns and the grey level run length matrix. This method of option extraction makes extensive use of distant leaders, in-intensity sub-size characteristic search, and adjustable acceleration factors. The function optimization was carried out using the random acceleration coefficients and the sine and helix model in two-stepped forward particle swarm optimization. By combining GLCM with HOG, Vidya, M., and Maya V. Karki were able to extract textural elements. [10] They enhanced the skin lesion images' quality and got rid of distracting components like skin and hair color. Geodesic Active Contour was combined with SVM, KNN, and Naive Bayes to categorize the lesion component into benign and malignant conditions (GAC). A method for extracting attributes was proposed by Pham, Tri Cong, and others. Local Binary Pattern, Scale-Invariant Feature Transform, Histogram of Oriented Gradients, and Hue Saturation Value are only a few of the methods used by [11] to analyze images. The input photographs were pre-processed using Gaussian blur, linear normalization, and a combination of the two to reduce noise. The balanced Random Forest classifier was used to classify benign and melanoma tumors with an accuracy of 74.75%. Glaister et al. used combined statistical texture distinctiveness to separate melanoma skin cancer pictures. However, this approach has a number of significant drawbacks, including the small amount of data it produces, which significantly reduces the classification's performance [12]. The authors of the study have presented a novel technique for the segmentation and bracketing of skin lesions. For segmentation, it is based on a region-growing system, and for bracketing, on SVM, KNN, and SVM and KNN emulsion. Despite producing correct bracket results, the constructed method has a lot of drawbacks, especially when it comes to the need for human participation in the description of the number of clusters [13]. A computer-backed opinion system with efficient algorithms was proposed by Kass et al. to categorize and read cancer. The suggested method uses differential limited adaptive histogram equalization and median filtering to improve the prints. Regularized Otsu's Segmentation, which forms the segmentation algorithm's basis, is designed to discriminate between damaged skin lesions and healthy skin. The bracket phase is built using monstrous AdaBoost-Support Vector Machine techniques and neural networks. The key flaw in the presented technique is that it necessitates a large amount of data for literacy, which isn't always feasible [14].

The research of skin cancer utilizing noninvasive techniques like image processing has recently been one of the most exciting and delicate areas of study. Towel counter analysis is a technique used by Wiltgen et al. that is based on the division of an image into equal-sized square elements, from which features are also calculated. The distinction between homogeneous and significantly different or luminous towel portions can be made using the gray position-occurrence matrix and argentine position histogram features. This technique resulted in the fashionable bracket delicacy of 92.7 [15]. The Multi-Parameter Birth and Bracket System was created by Fatima et al. to aid in the early detection of carcinoma of the skin. The method uses a six-phase system to extract 21 features from the image that was recognized. Statistical analysis is performed after these qualities have been eliminated [16]. Patwardhan et al. presented a method for examining and classifying skin lesion images into cancer and dysplastic nevus based on the use of a tree structure model anchored in marine metamorphosis. The recommended tree structure model would semantically describe the texture data and spatial frequency data that were gathered from the skin lesion photos [17]. Doukas et al. developed a smartphone-based system to store skin area image captures, identify a region of interest, and also evaluate your own prints. Using a mobile operation, the system gathers intelligence from skin images, recognizes them, and classes them as cancer, nevus, or benign lesions based on how abrasive they are. Two of the system's 11 classifiers, the multilayer perceptron, and the support vector machine, are tied for the highest delicacy with scores of 77.06 and 75.15, respectively [18].Hamd and Asa used color manipulation to predict skin cancer. To analyze the hues of skin lesions, they employed a digital approach based on symmetric color. [19]. Data collecting was the lesion's leading edge at first. Preprocessing By the point of birth-based diagnosis and segmentation. For each image, the harmony position was determined in order to detect benign excrescences. It was also determined to calculate the symmetric parameters. Three different skin lesions, including carcinoma, rudimentary cell melanoma, and scaled cell melanoma, could be recognized thanks to the photos. Two strategies for adjusting to skin lesions were developed in this investigation. In order to acclimate, artificial diapasons in sanguine, unheroic, brown, and black colors were first used. The alternative method entailed altering a database of beneficial and harmful tints.

The 40 prints were compared to the issues. The bracket values for the first and alternative routes were 80 and 92.5, respectively. However, the outcomes will be superior.

The JSEG algorithm was originally used to establish the lesion boundaries in [20]. GLCLM was utilized to extract two characteristics, such as color and texture, and SVM classification was then used to diagnose malignant lesions. When used on a database of 655 thermoscope images, the results showed that the system had a 90% accuracy rate.

2.3 Comparative Analysis and Summary

In this case, we can see that the results of our model are the highest compared to other cancers, which proves the acceptability of our model

2.3.1 Comparative Table

TABLE 2.1: COMPARATIVE TABLE

Author	Algorithm	Performance Measure	Data Set
Our Model	densenet201	97%	HAM10000
Reda Kasmi et.al. [26]		94.0 % Accuracy	
Swati Jayade et.al. [27]	SVM	94.05% Accuracy	
Nazia Hameed et.al. [28]	ECOC SVM	86.21%	PH2 ISIC DermIS DermQuest
Lokesh Singh et.al. [29]	SVM	92.5% Accuracy	PH2

2.4 Scope of the Problem

This skin cancer is more dangerous than basal cell carcinoma (BCC) and squamous cell carcinoma (SCC) while being less common because it can spread to other organs more quickly if left untreated. Learn more about the several melanoma types, risk factors, causes, symptoms, and treatments.

2.5 Challenges

The most challenging aspect of this research is finding the appropriate dataset. On the internet, there are many datasets, however, most of them are uneven. Not least of all, we selected the HAM10000 dataset. Despite the fact that this dataset is uneven as well, we decided to use it because we wanted to improve the results. Training the model created further challenges. because of how weak our GPU configuration was.

CHAPTER 3
Research Methodology

3.1 Introduction

The pre-processing, noise reduction and transfer of the data into the appropriate format for Tensor Flow training comprise the first portion of this session. After the training phase, look over the certified photos and send them for testing. In addition, we randomly select which test image to display.

3.2 Research subject

The term "research subject" refers to the participant in the study. The person will aid in answering the research topic, whether through a machine or a mental experiment. Sometimes, volunteers, participants, or human subjects are used in the study. Patients with tonsil cancer served as my subjects on this occasion. The subject was further refined into information that computers can comprehend.

3.3 Data Collection Procedure

Collection HAM10000 Dermatoscopic filmland was gathered from colorful populations using colorful modalities for admission and storage. The final dataset, which may be utilized as a training set for academic machine literacy, consists of 10015 dermatoscopic images. Significant individual orders present in the instances include dermatofibroma, actinic keratoses, intraepithelial melanoma/complaint, Bowen's rudimentary cell melanoma, benign keratoses such as lesions, carcinoma, melanocytic nevi, and vascular lesions. Histology confirms more than 50 lesions; the other cases are supported by additional study, expert judgment, or in-vivo confocal microscopy. There are numerous prints of lesions in the file.

Table 3.1: Detailed statistics of image collection

Label	No Of images	Image Format
Actinic Keratoses	327	Jpg
Basal Cell Carcinoma	514	Jpg
Benign Keratosis	1099	jpg
Dermatofibroma	115	Jpg
Melanoma	1113	Jpg
Melanocytic Nevi	6705	Jpg
Vascular Lesions	142	Jpg

3.4 Statistical Analysis

The study of statistics focuses on learning from data. Understanding statistics enables us to gather data properly, make wise judgments, and accurately communicate the outcomes. Making forecasts, doing scientific research, and using data to guide our decisions all need the use of statistics. We can comprehend a subject better thanks to statistics. Statistics significance is represented graphically by a bell curve. This article discusses the two primary reasons that statistics are so crucial to contemporary society. First and foremost, statisticians serve as guides for learning from data and eliminating common problems that could result in incorrect conclusions. The importance of data-driven decisions and perspectives is our second key argument.

3.4.1 Flow Model

We first started gathering data. The data subsequently underwent a variety of pre-processing procedures. The model is then trained using the pre-processed data. Then, several CNN models are used to predict.

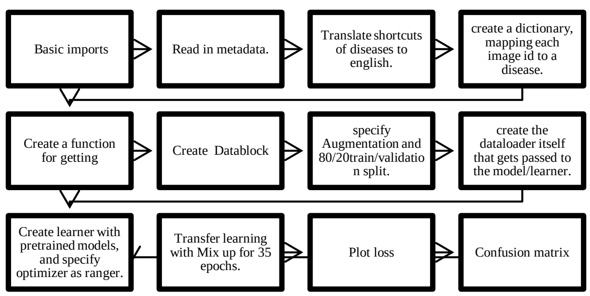

Figure 3.2: Flow Chart Model for Predicting survivability

3.5 Proposed Methodology

Resnet18

There are numerous types of ResNetXX infrastructures, where "XX" stands for the number of layers. ResNet18 has 18 levels since each network subcaste is identified by a number. There are around 11 million trainable parameters in ResNet18. Three-by-three-inch fortifications and CONV levels are present. Only two pooling layers are employed at the beginning and end of the network to provide identification linkages between each brace of the CONV position. [21]

Resnet50

The finest deep CNN design to use residuals is ResNet-50, a 50-estate architectural deep CNN armature, which we began understanding in 2015. ResNet-50, which has improved at measuring computer vision tasks, has won the 2015 ImageNet Big Scale Visual Recognition Challenge and the 2015 Microsoft Common Objects in Context competitions. Using 1.28 million training images spread over 1000 classes, the ResNet-50 small produced a top-five error average of 5.25. [22]

VGG-19 bn

A deep neural network that functions on various layers is the visual figure group network. The VGGNet, a CNN-based model, is applied to the ImageNet dataset. The VGG-19 is helpful since it is easy to use and has three convolutional layers stacked on top of each other that get deeper over time. Maximum-pooling layers were used by the instructor in VGG-19 to reduce the volume size. Two FC layers were employed, totaling 4096 neurons. [23]

DenseNet-201

DenseNet-201 received the forward connections between each sub caste and each posterior sub caste. [24]. The layers of the model include a global normal pooling sub caste, batch normalization, ReLU, one maximum pooling, three average pooling, depth consecution, an entirely linked SoftMax, and bracket layers. The model's convolutional, SoftMax, and bracket layers are among its layers, and the picture input sub caste size is 224 224 3. Overall, there are 805 links and 708 layers.

Squeezenet1 1

SqueezeNet [25] starts with one complication subcaste (conv1), goes on to include eight fire modules (fire2-9), and then adds a final complication subcaste (conv10). After the layers Conv1, Fire4, Fire8, and Conv10, SqueezeNet does maximum pooling with a stride of 2. These pooling placements, which were considerably delayed, were established in accordance with Section 3's Strategy 3.

3.5.1 Data Pre-processing

Translate illness abbreviations into English. • Create a vocabulary that associates each image identifier with a disease. • Design a function that retrieves the label. • Create a data block, specify data augmentation, and divide the data 80/20 between training and validation. • After that, make the data loader, which is given to the learner or model.

3.5.2 Performance measurements

Following the creation of the models, the relevant anonymous data is used to compute the accuracy, F1 score, precision, recall, classification report, and confusion metrics. We consulted the confusion matrix for assistance with this. A table called a confusion matrix can be used to evaluate how well a classification system performs. A confusion matrix is a useful tool for evaluating and summarizing the efficacy of a categorization system. From the confusion matrix, we derive true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). We can compute accuracy, theory, F1 precision, recall, and specificity using these measurements. The results are kept to themselves in a separate area after the calculation is finished. F1 = (precision + recall) / (precision + recall) / (2*precision*recall) (TP + FN) / TP = recall Accuracy = (TP + TN) / (TP + FN + TN + FP) Specificity = (TP + FP) / (TP + FP) (TP + FP) (TN + FP) / TN = Precision. The AUC (area under the curve) score and ROC (receiver operating characteristic) curve were also used to examine the results. We have employed numerous techniques and plans of action. We go into great detail on how we succeeded in attaining our objectives.

3.6 Implementation Requirements

- Laptop
- Internet Connection.
- Kaggle.
- Python Environment.
- Fast-ai.

CHAPTER 4

Experimental Results and Discussion

4.1 Experimental Results & Analysis

In order to determine whether a patient has melanoma skin cancer, we aimed to build a model utilizing fast-ai CNN techniques. Deep learning methodologies have been used to create a wide variety of prediction models. The most effective plan must be identified after taking the data into account. The training of used infrastructures uses 10015 images. In 35 years, the training process is over. Figure 4.1, 4.2, 4.3, 4.4 and4.5 depicts the confusion matrix.

4.1.1 resnet18

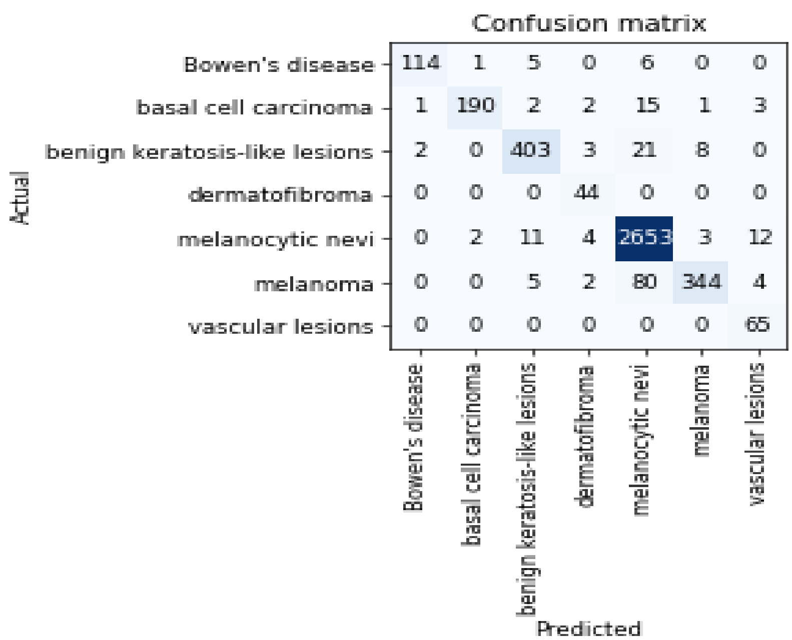

Figure 4.1: Confusion matrix(resnet18)

4.1.2 resnet50

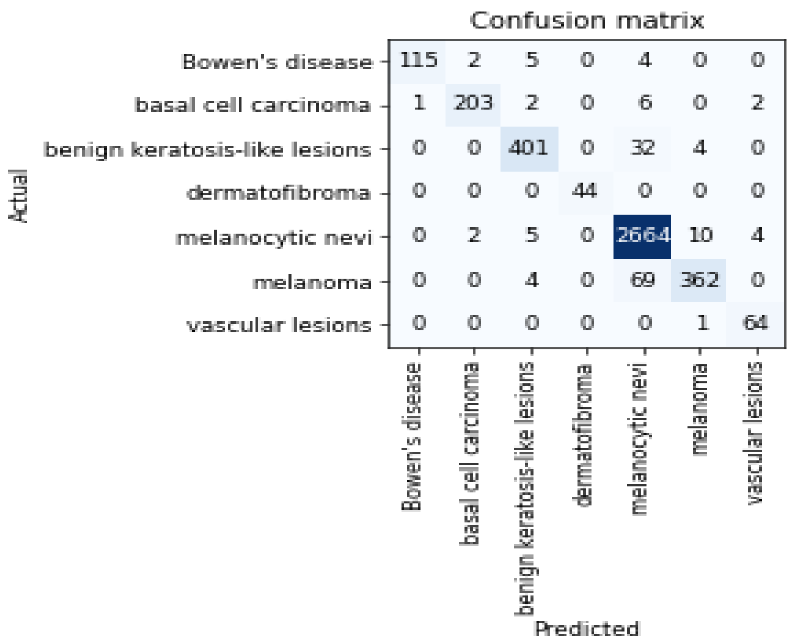

Figure 4.2: Confusion matrix(resnet50)

4.1.3 vgg19_bn

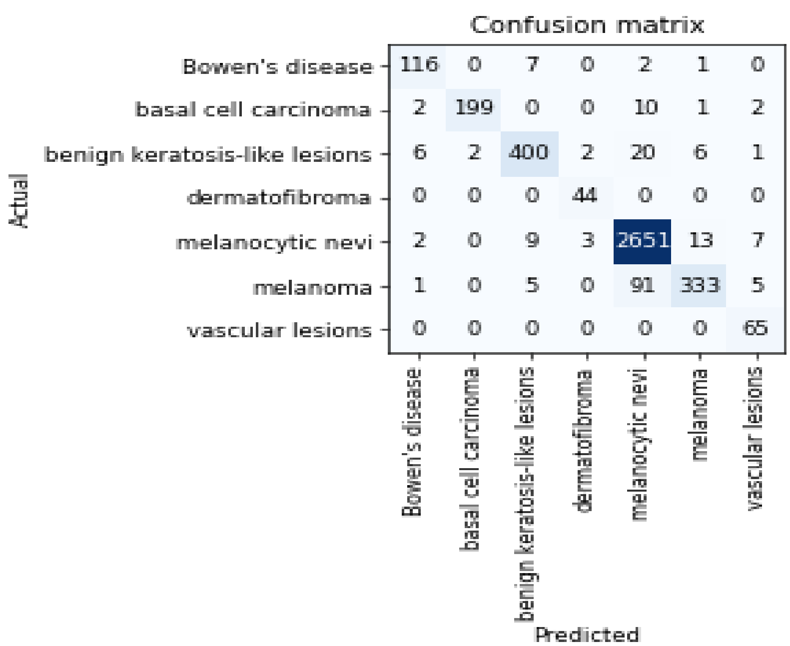

Figure 4.3: Confusion matrix(vgg19_bn)

4.1.4 densenet201

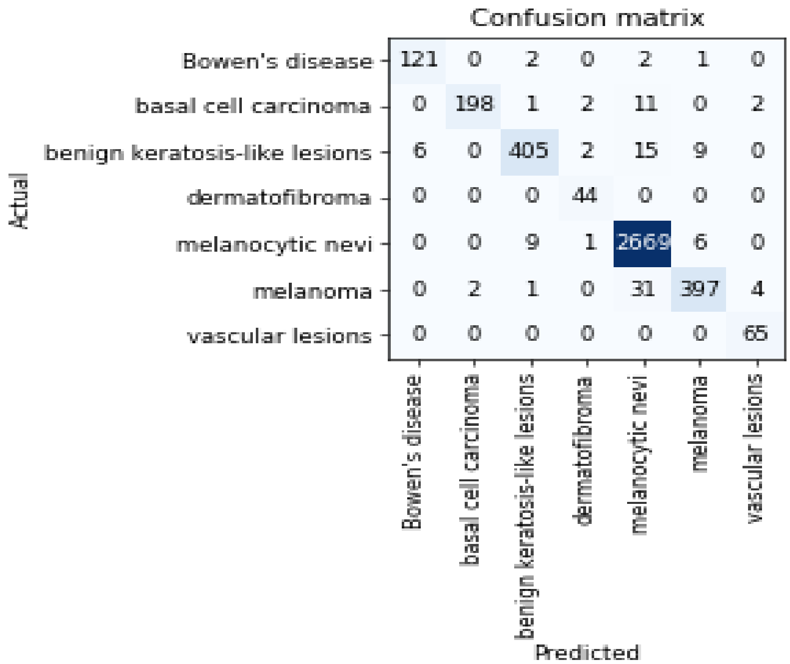

Figure 4.4: Confusion matrix(densenet201)

4.1.5 squeezenet1_1

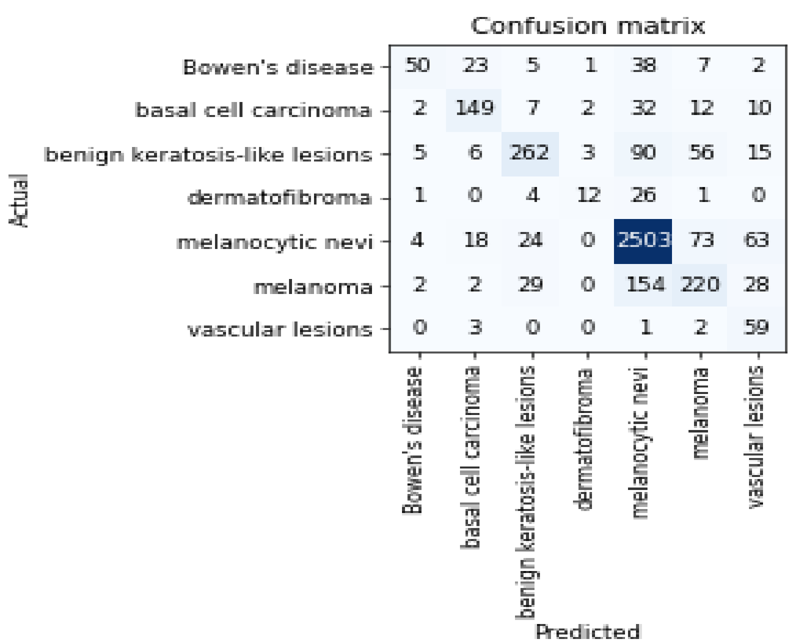

Figure 4.5: Confusion matrix(squeezenet1_1)

4.1.6 Performance Measurement Table

Table 4.1: Classification report (melanoma)

pre-trained models	precision	recall	f1-score	Support
resnet18	97%	79%	87%	435
resnet50	96%	83%	89%	435
vgg19_bn	94%	77%	84%	435
densenet201	96%	91%	94%	435
squeezenet1_1	59%	51%	55%	435

Table 4.2: Classification report(melanoma)

pre-trained models	accuracy
resnet18	95%
resnet50	96%
vgg19_bn	95%
densenet201	97%
squeezenet1_1	81%

4.2 Result & Discussion

The training of used infrastructures uses 10015 images. The training procedure will be completed in 35 years. Figure 2 shows the confusion matrix for densenet201, and Figure 3 shows the plot loss of the model graph. The classification report for melanoma for the resnet18, resnet50, vgg19 bn, densenet201, and squeezenet1-1 models is shown in table 1. Table 2 displays the accuracy results for the resnet18, resnet50, vgg19 BN, densenet201, and squeezenet1-1 networks.

CHAPTER 5
Impact on Society, Environment and Sustainability

5.1 Introduction

Melanoma is a type of skin cancer that arises from the pigment-producing cells in the skin. It is the most aggressive and deadly form of skin cancer and can spread to other parts of the body if not treated in its early stages.

5.2 Impact of society

The use of convolutional neural networks (CNNs) for the early detection and diagnosis of melanoma has the potential to significantly impact society in a number of ways. First and foremost, the use of CNNs for melanoma detection can potentially save lives. Early detection is crucial in the treatment of melanoma, as it is much easier to treat it in its early stages before it has had a chance to spread to other parts of the body. By using CNNs to analyze images of the skin and identify potential melanoma lesions, doctors can catch the disease at an early stage and begin treatment immediately. This can not only improve the chances of successful treatment, but it can also reduce the cost and burden on the healthcare system as a whole. In addition to the medical benefits, the use of CNNs for melanoma detection can also have a positive impact on society in terms of cost and convenience. Traditional methods for detecting melanoma, such as biopsies and other invasive procedures, can be time-consuming and expensive. In contrast, the use of CNNs can provide a quick and cost-effective method for detecting melanoma, allowing more people to access early detection and treatment.

5.3 Impact of Environment

The use of CNNs for melanoma detection also has the potential to have a positive impact on the environment. By reducing the need for invasive procedures, such as biopsies, the use of CNNs can help reduce the overall consumption of resources, including energy, water, and materials. This can help reduce the environmental impact of healthcare and contribute to the overall sustainability of the healthcare system.

5.4 Ethical Aspect

Ethically, the use of CNNs for melanoma detection raises a number of questions and concerns. One of the main concerns is the potential for bias in the algorithms used to analyze the images. If the algorithms are not properly trained or validated, they may be more likely to misdiagnose melanoma in certain groups of people, leading to inequitable access to care. It is important for researchers and developers to take steps to address and mitigate these potential biases in order to ensure that the use of CNNs for melanoma detection is ethical and fair.

5.5 Sustainability Plan

In conclusion, the use of CNNs for melanoma detection has the potential to have a significant impact on society, the environment, and the ethical aspect of healthcare. By providing a quick and cost-effective method for detecting melanoma, the use of CNNs can save lives and improve the overall sustainability of the healthcare system. However, it is important to address and mitigate potential biases in the algorithms in order to ensure that the use of CNNs is ethical and fair.

CHAPTER 6
Summary, Conclusion, Recommendation and Implication for Future Research

6.1 Introduction

This chapter covered how the project's potential can effectively support the organization's future growth. A more efficient way might be created using future technologies. A pleasant and orderly conclusion is presented at the end of this chapter. A list of the references is provided at the conclusion of this chapter.

6.2 Implication for Further Study

To ensure that no crucial data is lost, we will collect significant amounts of data from a huge number of highly reputable sources and utilize an efficient pre-processing technique. Analyze more strategies for handling uneven data. We implemented new machine learning algorithms and identified highly correlated features in order to get better results. For other tumors, we also want to perform identical studies.

6.3 Conclusions

Over the past few years, the incidence of skin problems has progressively climbed, and melanoma's prevalence and mortality rates have had a significant negative impact on people's health. Professionals find it challenging to identify melanoma early and treat it aggressively; occasionally, even when given the same dermoscopy images, different experts may arrive at different conclusions. As a result, skin cancer classification research is critical for skin cancer auxiliary diagnosis. This work focused on classifying skin lesion images using the HAM10000 and evaluating the produced image data. Due to the uneven distribution of the image samples, we first processed the data. The experimental results also show that preprocessed photographs have a higher degree of categorization accuracy. For categorization, Resnet18, Resnet50, Vgg19 BN, Densenet201, and Squeezenet1-1 are employed. The results shown in Figures 2–9 show that Resnet–34 and ResNet–18 were completed with an accuracy of 98%. Our main goal was to use the same settings to compare the results of various CNN designs. In the future, we'll put a ton of novel ideas to the test in search of the skin cancer classification that is most accurate.

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