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Convolutional Neural Network Approach for Early Skin Cancer Detection

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Abstract: - The field of medical image processing is rapidly adopting artificial intelligence. Its use is required for many applications in the healthcare industry. A machine can learn from experience without explicit programming thanks to computer education. It is an area within AI. Deep learning, a kind of machine learning, infers critical features for image processing via multiple layer processing and mathematical operations based on artificial neural networks. In the field of healthcare, which encompasses medicine and dentistry, artificial intelligence has several applications.Early melanoma skin cancer identification is necessary for effective therapy. Melanoma, among the various types of skin cancer, has recently gained international recognition as the most deadly one since it is much more likely to spread to other body regions if detected and treated quickly. Clinical diagnosis of various ailments is increasingly using non-invasive medical computer vision or medical image processing. These methods offer an automatic image processing tool that makes it possible to examine the lesion quickly and precisely. The procedures used in this study included building a database of dermoscopy images, preprocessing, segmenting using thresholding, extracting statistical features using asymmetry, border, colour, diameter, etc., and choosing features based on the total dermoscopy score, principal component analysis (PCA), and convocation neural network classification (CNN). According to the findings, a classification accuracy of 90.1% was attained.

Keywords: AlexNet, Benign, Convolutional Neural Network, Data pre-processing, Feature extraction, Image Augmentation, Malignant, Maxpooling , Training, Testing, Resnet, VGG.

I. INTRODUCTION

Dermatologists refer to the vast majority of changes to human skin as rashes. A potentially malignant cause or a non-cancerous reason could be responsible for skin changes[1].

Human skin cells experience aberrant development when exposed to the sun's UV radiation. In parts of the skin that are overexposed to the sun's harmful UV radiation, cancer cells grow and multiply. Skin cells have their DNA changed, which causes the process of mutation to propagate throughout the cells and cause them to proliferate out of control into a mass of cancer cells.Skin rashes and skin cancer warning indicators, include persistent, scaly, pink or red plaques,Itching can occasionally happen to the same person. Skin rashes can appear for less specific reasons than skin cancer, but this is uncommon. Rashes often fade away over time, however skin cancer c[1]ells do not respond to standard therapies and quickly move to other places of the skin. In opposition.Despite the difficulties outlined in the problem description above, research on the identification and detection of the caries disease is currently ongoing. Over time, many different tactics have been evolved.The computerised grading of skin diseases can aid in identifying skin conditions as they advance and encourages early contact with medical experts to receive the necessary medical care.several studies employing digital images in relevant fields Medical professionals can employ processing for the detection and classification of skin malignancies as a technique to more quickly and accurately diagnose skin illnesses.[3]Launching a powerful deep learning technique that would result in a powerful reaction is therefore essential. methodology In the context of medical imaging, a CNN-based technique is utilised to identify skin cancer. One disadvantage of CNN-based approaches is the requirement for many datasets to train the computer on such models. Another disadvantage is the length of time required for intensive picture processing and the need for powerful computers (GPUs).Environmental elements, including those that cannot be prevented, such as distinct plant backdrops when taking pictures, variations in lighting, and other environmental issues, may have an impact on the outcomes and evaluation methods. We can identify this issue and improve the productivity and sustainability of caries detection when technological innovation is accelerated and complete infrastructure is available. The model will provide the

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capabilities required to start real-time skin cancer detection once the expected findings are successfully achieved.[4]

In the second section, we talk about the literature survey we did using the sources we used.The project's methodology is then step-by-step detailed.Then, using Kaggle-sourced we used three different datasets.The resulting findings, where we measured accuracy, loss, and learning rater against epoch, are then displayed.The software requirements that we utilised to execute the model are then provided. Finally, the study is completed with a list of references.

II. LITERATURE SURVEY

The Convolutional Neural Network (CNN) used to create the suggested model is presented in this section.CNN, or Convolutional Neural Network A convolutional neural network is a deep learning technique that uses convolutional operations rather than matrix multiplication to retrieve input visual pictures. Its structure resembles that of the human brain. It manages the input imagery more skillfully. Through the employment of the proper filters, it successfully comprehends the spatial and temporal dependencies from the supplied images.[3]

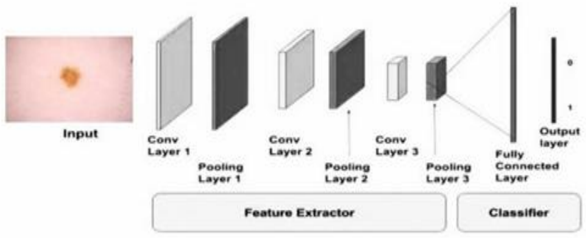


Figure. 1 Working of CNN

Figure 1 depicts the architecture of CNN, which consists of an input layer, a pooling layer for a number of convolutional layers, a fully connected layer, and an output layer.

This section covers the many methods for identifying caries using different image processing techniques.

Skin cancer is among the most prevalent and dangerous diseases in the world. Uncontrolled cell growth in the skin tissues is what causes the disease. Early identification is essential for the successful treatment of skin cancer. Early skin cancer diagnosis typically involves the use of CT, MRI, and other imaging modalities. Medical image mining is a promising field of artificial intelligence that analyses patient records automatically to find new information that may be helpful for making medical decisions. We'll start by using a few methods, including preprocessing, feature extraction, and rule development, which are critical to the process of mining medical images. Digital X-ray chest films are split into two categories by the methods utilised in this study: abnormal and normal. A healthy patient is believed to be in a normal state. In order to classify the aberrant condition, which includes the many types of skin cancer, neural networks, a machine learning technique, will be applied. We'll also look into applying association criteria to categorise x-raychest films. For use in medicine, the digital x-ray chest films are kept in enormous multi-media databases.This multimedia database offers a great starting point for extracting the required information and subsequent rules from the database in issue utilising picture recognition techniques. These suggestions, which we were able to obtain using photo recognition techniques, will aid the physicians in making crucial choices in relation to a certain patient scenario.[1] This decision was made in consideration of the potential for lung nodules in specific areas. After the divided area has been processed with an easy multiscale procedure to make the nodules more visible, an extraction strategy is then employed to choose potential nodules. [2] A discrete feature space is necessary for many supervised machine learning techniques. In this essay, we examine earlier research on continuous feature discretization and pinpoint the specific features of the approach. Then, in order to find the traits that are most crucial for classification, we suggest a novel supervised approach that combines discretization and feature selection. Associative classifiers should be utilised as the classification method. Harlick Texture features that were taken from MRI scans make up the features that are utilised. The findings demonstrate that the provided approach is workable and suitable for preprocessing continuous valued variables.[3]Using data mining classification techniques The leading cause of death for both men and women is cancer. Early cancer detection can aid in the total eradication of the disease. Therefore, methods for early cancer nodule detection are becoming more and more important.Lung cancer is commonly given the incorrect diagnosis. Lung cancer may result in extra serious issues that speed up mortality if it is not detected in the early stages. Early detection and diagnosis of the condition are crucial for determining prognosis and the chance of a cure.A diagnostic error is one of the most frequent instances of medical malpractice done globally. the commercial and scientific realms, data mining and knowledge discovery have various applications. The use of data in healthcare system can produce insightful information. The potential application of classification-based rule-based, decision-tree, naive bayes, and artificial neural network data mining approaches to enormous volumes of data is briefly discussed in this article. [4]In order to mimic how millimetre waves interact with human skin and skin malignancies, this study suggests creating new, reliable, and broad-band skin equivalent semisolid phantoms. In order to assess the practicality of cutting-edge technology and enhance design ideas for millimeter-wave skin cancer detection systems, realistic skin phantoms are an essential tool.With the right proportions of deionized water, oil, gelatin powder, formaldehyde, TX-150 (often referred to as "super stuff"), and detergent, normal and cancerous skin tissues can be independently regenerated. Using a millimeter-wave vector network analyzer and a slim-form open-ended coaxial probe, the dielectric characteristics of the phantoms are examined over the frequency range of 0.5 to 50 GHz. Fresh, ex-vivo skin permittivities (both normal and malignant) exhibit excellent agreement with the measured permittivity values across the whole frequency range. The findings of this investigation revealed that substitute human skin tissues were the most closely related among all the phantoms described in the literature. The durability of dielectric characteristics over time is also looked at. The phantoms exhibit long-term stability and have been tested for up to 7 months.It is also established how deeply millimetre waves penetrate phantoms of healthy and cancerous skin. It has been shown that the vast majority of the epidermal and dermal skin structures are affected by millimetre waves because of how deeply they penetrate human skin (0.6 mm on average at 50 GHz).[5]The paucity of data, especially the annotated data that supervised learning algorithms often require, is one of the primary reasons why deep learning technologies for cancer diagnosis have been implemented slowly. In this paper, a Convolutional Neural Network (CNN) for skin cancer detection is presented. The basic database of the International Skin Imaging Collaboration (ISIC), which is utilised to train the CNN algorithm, consists of 50 benign and 47 malignant members.A Generative Adversarial Network (GAN) is created to produce fictitious images of skin cancer in order to make up for the lack of data needed to train the suggested CNN algorithm. Without the generated synthetic images, the classification performance of the first trained CNN is roughly 53; however, when the generated synthetic images are added to the primary database, the model's performance is enhanced to 71.[6]Early melanoma skin cancer identification is necessary for effective therapy. Melanoma is the most serious type of skin cancer because it has the most potential to spread to other parts of the body even with early detection and treatment. Clinical diagnosis of various ailments is increasingly using non-invasive medical computer vision or medical image processing. These methods offer a tool for automatic photo processing that makes it possible to evaluate lesions quickly and precisely.Dermoscopy picture database gathering, preprocessing, segmentation using thresholding, statistical feature extraction using a Grey Level Cooccurrence Matrix (GLCM), along with asymmetry, border, and colour, are the techniques included in this work. To choose characteristics, principal component analysis (PCA) is utilised, among other features, such as diameter and (ABCD). The data is then categorised using an SVM after the total Dermoscopy Score has been determined. According to the findings, 92.1% classification accuracy was attained

III. METHODOLOGY

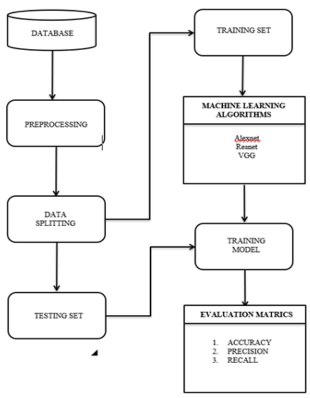


Figure. 2 System Flowchart

Fig 2. is about the flowchart of the working model with step by step process of image classification.

3.1 Pre-processing and Dataset Creation:

The first step will be to create a dataset that has several, top-notch images of each skin cancer-related scene.Both benign and malignant skin cancer images can be found id heavily on the clarity and quality of the images that are taken. The Dataset is pre-processed to remove any extraneous information and poor quality images after it has been prepared. Following that, the right type of skin cancer detection technique is used to identify each image.

3.2 Using a neural network for training:

Training the neural network on the dataset to memorise each image and its associated name is the most crucial step in the process. To achieve the intended results, it is crucial to conduct the training using high-quality data and to give it enough time. Each unique photo provides input to the neural network, and the encoding is saved for comparison at a later time.During the training phase of the convolutional neural network, the weights and biases in the convolutional and ReLu layers are adjusted. The image on the network starts to "remember" as a result. Once the Neural Network has done training, we can begin testing the model for predicting the type of skin cancer pictures are modified throughout the training phase. This causes the image to "remember" on the network. We can start testing the model for prediction of kind of skin cancer photos once the Neural Network has finished training.

3.3 Testing the model for skin cancer detection:

Once the neural network has been trained, we can start putting the skin cancer images to the test.The photograph featured every student who was present in the class at the time. The trained neural network is then fed the pre-processed image as an input. As we continue with image processing, the image is then binarized, turning it into a grayscale image.Because grayscale photos are the only ones that the computer can understand, feature extraction must be done in order to better identify the image. In "cnn prediction," after selecting "image preprocess," we ascertain if the cancer in the image is benign or malignant.

Pretrained Models Used

Alexnet:-At the ImageNet Large Scale Visual Recognition Challenge in 2012, the AlexNet architecture was unveiled.

-It was created by Alex Krizhevsky and published with Illya Sutskever and Dr. Geoffrey Hinton, Krizhevsky's dissertation advisor.

-AlexNet used the ReLu activation function, a crucial advancement in deep learning, and included eight layers. Due to the fact that the gradient values were no longer constrained to a specific range, the vanishing gradient issue was solved.

-It was 4 times faster than earlier models and the first CNN model to use a GPU.

Advantages:-

-The first significant CNN model to incorporate GPU training was AlexNet. This made model training go more quickly.

-In comparison to LeNet, AlexNet has a deeper architecture (8 layers), making it more able to extract features. With colour visuals, it also performed admirably for the time.

-There are two benefits to the ReLu activation function utilised in this network. In contrast to other activation functions, it does not limit the output. This indicates that the loss of features isn't too great.

-Not the dataset itself, but the negative result of the summation of gradients is negated. As a result, since some perceptrons are not active, model training speed will be further increased.

Disadvantages:-

-This model's depth is quite small in comparison to other models used in this article, which makes it difficult for it to learn features from image sets.

-We can observe that compared to future models, it takes longer to obtain findings with more precision.

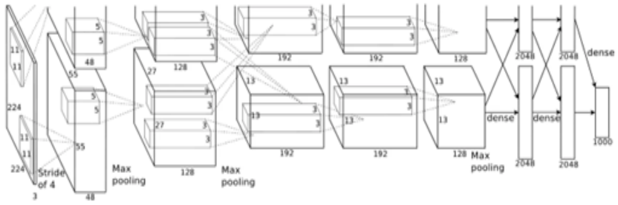


Figure. 3 Working of Alexnet

VGG:-A CNN architecture known as the Visual Geometric Group, or VGG, was released in 2014, two years after AlexNet. This model was introduced primarily to examine how depth affected accuracy while building picture classification and recognition algorithms.

Instead of using a single Conv layer with a big kernel size, the VGG network introduced the idea of grouping many convolution layers with smaller kernel sizes. As a result, there were fewer features at the output, and adding three ReLu layers rather than one increased the number of learning instances. The layered structure is followed by a pooling layer as can be seen in the Fig.

Advantages:-

-With the introduction of VGG, accuracy and speed both significantly improved. This was mostly caused by increasing the model's depth and adding pretrained models.

-Non-linearity increased with the number of layers with smaller kernels, which is always a good thing in deep learning.

-VGG introduced a number of structures based on related concepts. This expands our possibilities for the architecture that would work the best for our application.

Disadvantages:-

-We discovered that this model has a significant drawback known as the vanishing gradient problem. My validation loss graph makes it evident that there is an upward trend in validation loss. None of the other models had this problem. The ResNet architecture was used to resolve the disappearing gradient issue.

-The more recent ResNet architecture, which introduced the idea of residual learning another important innovation is faster than VGG

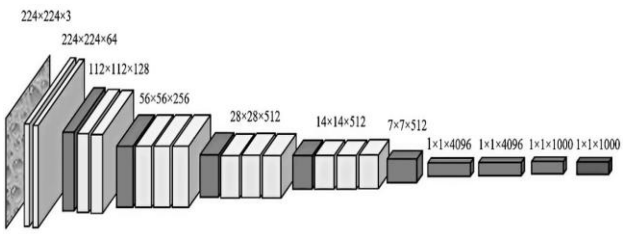


Figure. 4 Working of VGG

ResNet:- 2015 saw the introduction of ResNet, which significantly increased both accuracy and speed.In order to improve accuracy, VGG introduced the idea of adding layers. However, it was discovered that adding layers beyond 20 prevented the model from converging to the least error%. The issue of disappearing gradients is a significant contributor to this. The learning rate decreases to the point where the model's weights are not altered.The proliferation of gradients was a different issue. When Batch Normalisation was developed, this problem was resolved, but it still varies, albeit over a narrower range.To address this, the idea of residual learning which drew inspiration from the idea of lateral inhibition in the human brain was added. It simply means that brain cells have the ability to influence whether or not their nearby cells fire.Using a very straightforward example, residual learning may be described. When we first start to ride a bike, we make mistakes and gain knowledge. When we can ride a bike, our brain's neurons that help us learn the ability no longer fire, allowing us to concentrate on other aspects of riding a bike

Advantages:-

-Not every neuron in the ResNet design needs to fire at once. This significantly cuts down on training time and increases accuracy. After learning a feature once, it doesn't try to learn it again; instead, it concentrates on learning additional features. A very clever strategy that significantly enhanced the effectiveness of model training

-The deterioration issue was brought on by the intricacy of a similar VGG network, and it was resolved using residual learning.

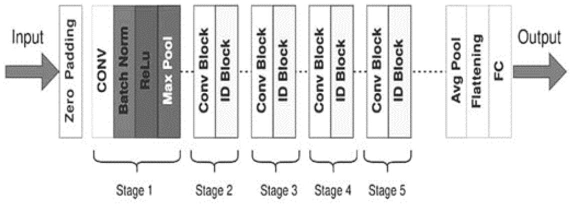


Figure. 5 Working of ResNet

IV. DATASET

We used three differnt public Skin Cancer dataset created by Kaggle over three pretrained models for this report and For the construction of the algorithm

Table 1. Classificatio of dataset

Table 1. describes the division persentage of dataset into Training ,Testing and Validation.

Dataset’s	Training	Testing	Validation
Dataset-1 (3000 images)	60%	20%	20%
Dataset-2 (5700 images)	60%	20%	20%
Dataset-3 (4200 images)	60%	20%	20%

Labelling and image preparation

Image dataset processing is a crucial step in the disease identification process for leaves, allowing everyone working in the field to more precisely and accurately produce crops that are disease-free. Pre-goal processing's main objective is to improve an image's qualities and stop any subsequent image-related problems from lowering the quality of the input photos. Environmental factors and human mistake result in an unclean and noisy raw dataset of images; these elements must be removed. Preparing images for training data models is known as "image pre-processing," and it includes techniques like resizing, cropping, orientation, rescaling, colour, and rescaling.The terms mean, median, wiener, as well as other novel algorithms, are used to describe a variety of image processing techniques. Whitening, normalisation, and standards-setting.[3] As a result, it is a method for enhancing the evaluation and analysis of an input image. Image annotation techniques like semantic segmentation annotation are currently used to identify photos and enable full identification of images so that objects may be seen more precisely.

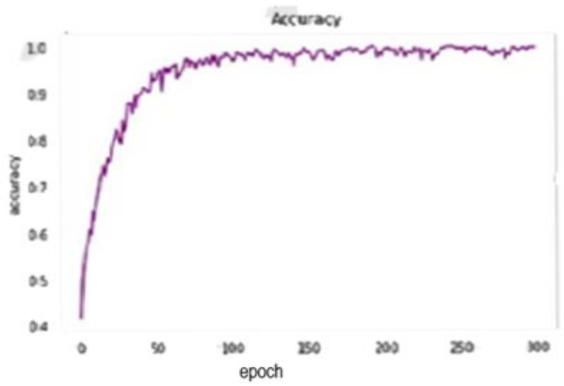
Feature extraction and image enhancement

A good method for generating more random training data from earlier training samples is image augmentation. It improves the model's robustness and generalizability. It is typically employed when there aren't enough data or when assembling a manageable dataset requires some time.Because of augmentation techniques like shifting, flipping, and rotating, each randomly produced image copy is unique from the others. Because of this, a small piece of code can generate enormous collections of identical images.The Image Data Generator class is used for augmentation in Keras. For augmentation, methods like rotation, brightness, zooming, flipping, and standardisation are used.The Image Data Generator class makes sure the model is continuously supplied with fresh variants of data in the form of images. Another advantage is that memory utilisation isn't very high. The step in the dimensionality reduction process when a preliminary raw picture collection is condensed and split into usable categories is referred to as feature extraction. To extract features, a statistical methodology is paired with particular image processing methods. The traits and qualities required by the leaf disease are taken into consideration. Assume, for instance, that the texture characteristics are retrieved after the colour features have been removed from the image dataset (GLCM). The characteristics of the conventional method, also known as GLCM, include homogeneity, correlation, energy, dissimilarity, and contrast. After that, feature selection is complete. In order to achieve the highest level of predicted accuracy, it is customary to select the most notable features from a series of images.

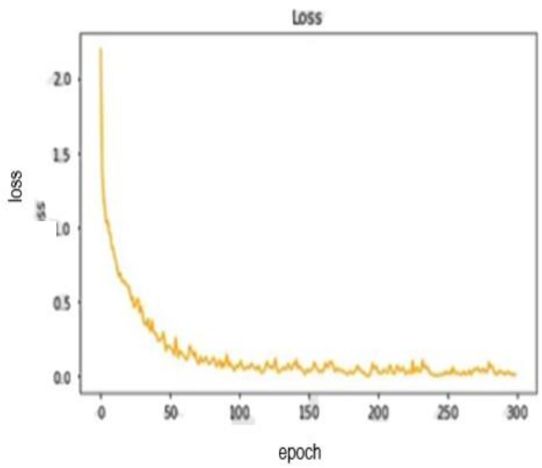
V. RESULTS

5.1 .Alexnet:-

For **Dataset 1**



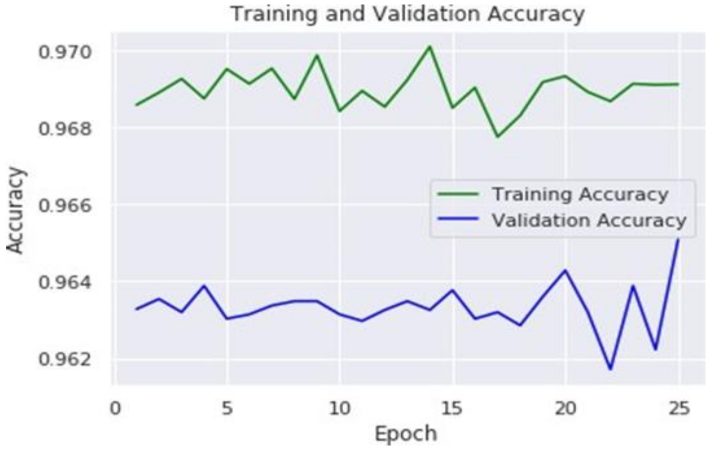
(a)



(b)

Figure. 6 Accuracy and Loss. (a) and (b) shows Accuracy and loss with respect to Epochs For dataset 1 using Alexnet.

Dataset 2-

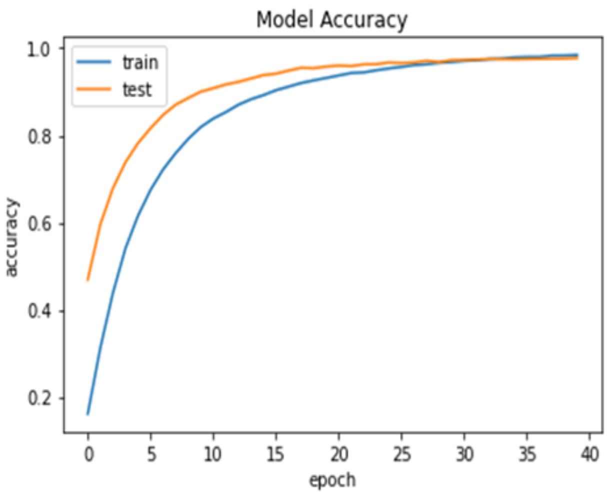


(a)

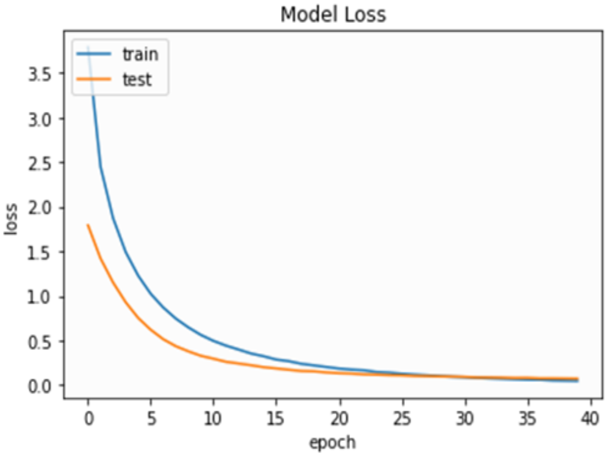
(b)

Figure. 7 Accuracy and Loss. (a) and (b) shows Accuracy and loss with respect to Epochs For dataset 2 using Alexnet.

Dataset 3-



(a)

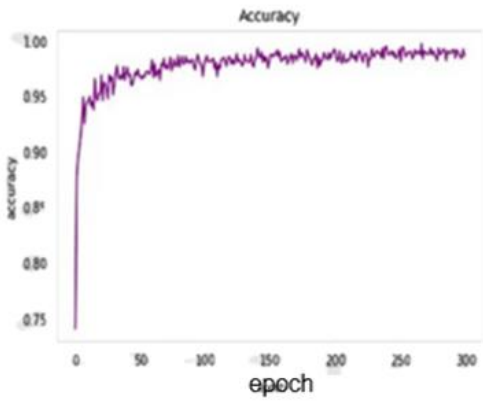


(b)

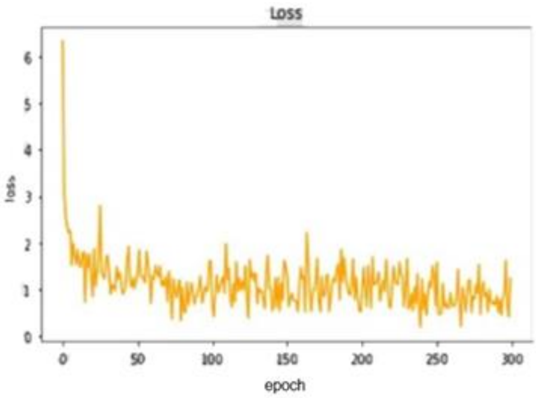
Figure. 8 Accuracy and Loss. (a) and (b) shows Accuracy and loss with respect to Epochs For dataset 3 using Alexnet.

5.2. - VGG:-

Dataset 1



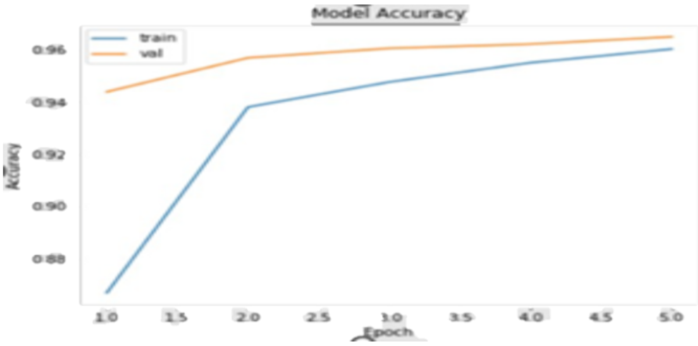
(a)



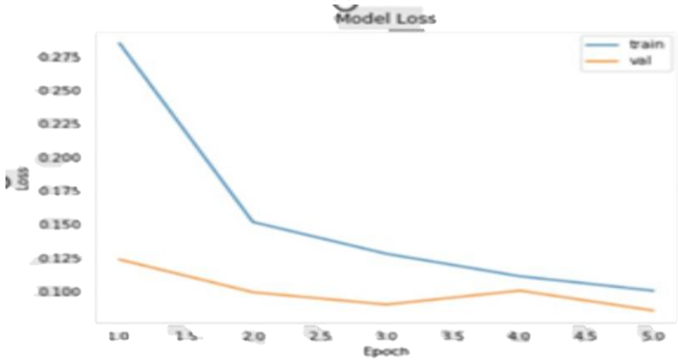
(b)

Figure. 9 Accuracy and Loss. (a) and (b) shows Accuracy and loss with respect to Epochs for Dataset 1 using VGG.

Dataset 2-



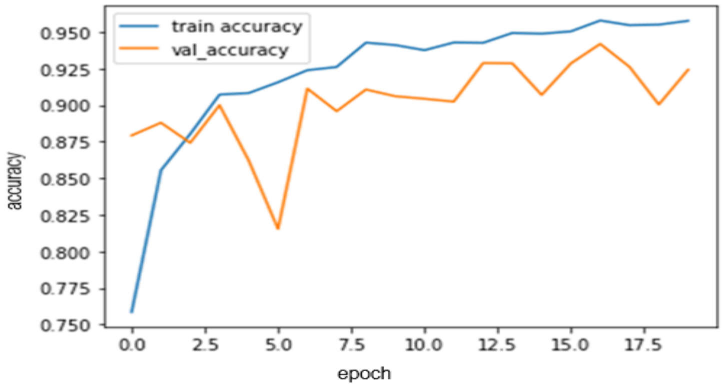
(a)



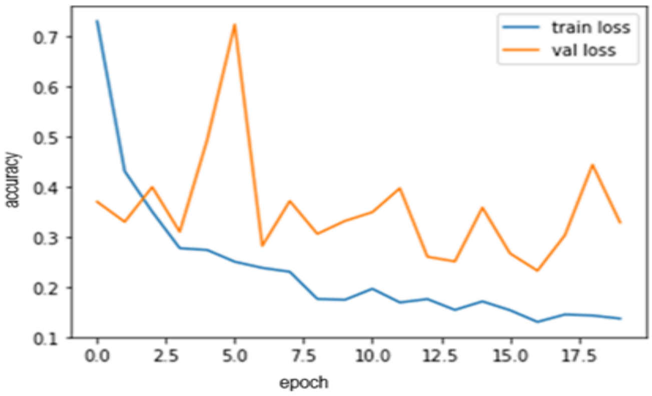
(b)

Figure. 10 Accuracy and Loss. (a) and (b) shows Accuracy and loss with respect to Epochs for Dataset 2 using VGG.

Dataset 3-



(a)

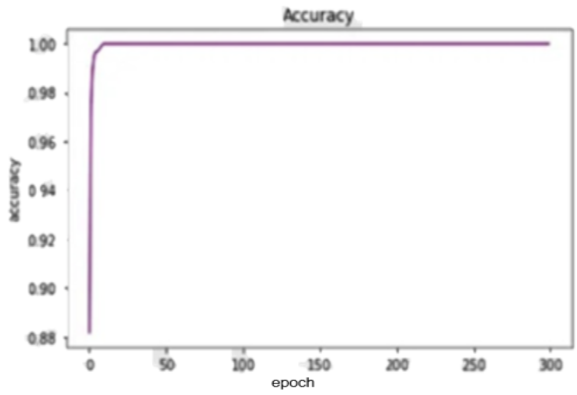


(b)

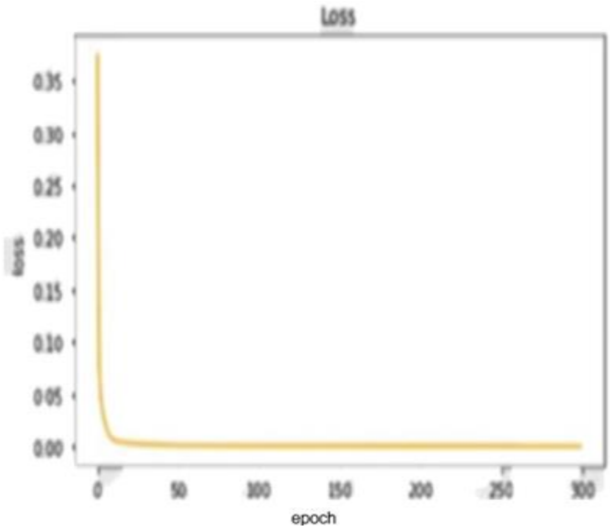
Figure. 11 Accuracy and Loss. (a) and (b) shows Accuracy and loss with respect to Epochs for Dataset 3 using VGG.

5.3. ResNet:-

Dataset 1-



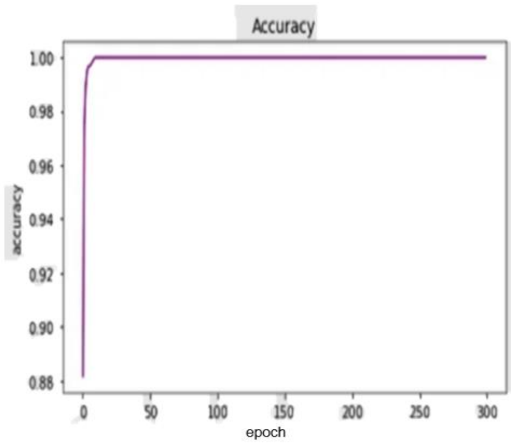
(a)



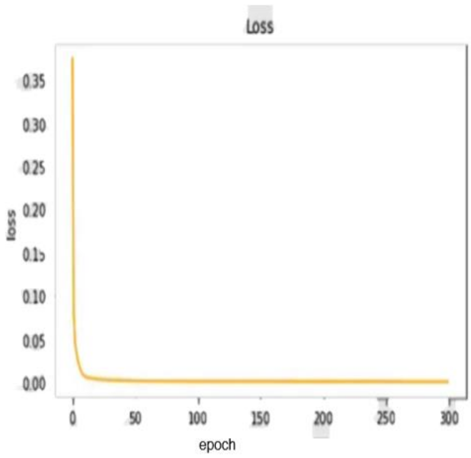
(b)

Figure. 12 Accuracy and Loss. (a) and (b) shows Accuracy and loss with respect to Epochs for Dataset 1 using ResNet.

Dataset 2-



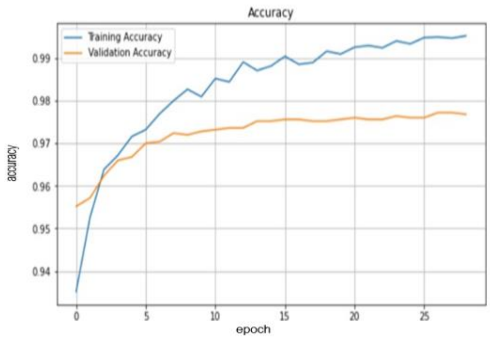
(a)



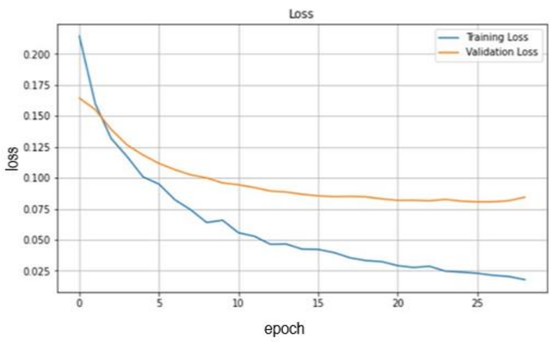
(b)

Figure. 13 Accuracy and Loss. (a) and (b) shows Accuracy and loss with respect to Epochs for Dataset 2 using ResNet.

Dataset 3-



(a)



(b)

Figure. 14 Accuracy and Loss. (a) and (b) shows Accuracy and loss with respect to Epochs for Dataset 3 using ResNet.

VI. SUMMARY

These three CNNs are ranked according to their accuracy on the Image dataset in the table below. You can also examine the quantity of trainable parameters and the FLOPs (Floating Point Operations) needed for a forward pass.

Table 2. Comparison Between All the Pretrained Models

This table shows the Accuracy comparison amongst all the three pretrained models.

Network	Accuracy	Parameter	FLOP	Epoch
Alexnet	84.5%	62M	1.5B	30
VGG	92.4%	138M	19.6B	30
ResNet	95.5%	60.2M	11B	30

There are several similarities to be made:

-Although AlexNet and ResNet-152 both contain roughly 60M parameters, their top-5 accuracy varies by about 10%. However, training a ResNet-152 takes more time and effort because it demands a lot of calculations (about 10 times as many as AlexNet).

-In comparison to ResNet-152, VGGNet not only has more parameters and FLOP, but also less accuracy. A VGGNet with worse accuracy requires more time to train.

-An AlexNet can be trained in around the same amount of time as Inception. With increased precision, the memory requirements are ten times lower (by around 9%).

VII. EQUATION OF ACCURACY

*Accuracy= (TP/(TP+TN))*100………….(1)*

Where,TP- True Positive

TN- True Negative

VIII. SOFTWARE SPECIFICATION

Machine learning, transfer learning, and deep learning libraries are used to install and implement the model. The CNN-based dental caries detection model is trained using a Tesla K80 Graphical Processing Unit.

Specifically, the Google Colaboratory's online, cloud-based spyder notebook.

Device Booster:

CPU: A 2.30 GHz, two-core Intel Xeon processor with 13.0 GB of RAM. 12 GB

IX. CONCLUSION

We conducted this experiment to learn more about the various CNN model types and how they affect the practical training of image classification models.As our pretrained models, we combined Alexnet,VGG, and Resnet with three different types of datasets containing various skin cancer photos of various sizes and pixel densities.The accuracy we obtained is given in the summary section up top, which claims that the ResNet model produces more precise answers.However, using it has certain drawbacks as well, such as the fact that it requires a lot of calculating and requires more time and work.It is possible to alter the number of photographs in the folder that can be selected. The size of the edited photos is calculated by converting each image label into a binary label and then saving it using pickle. Using the Image Data Generator tool, one can create smaller datasets with better outcomes by adding random.By using random shifts, flips, crops, and sheers, the Image Data Generator function can create smaller datasets with better outcomes.It takes a lot of time to train a network with a 30-epoch value.

X. CONFLICTS OF INTEREST

The authors declares that there is no conflict of interest regarding the publication of this paper.

XI. AUTHOR CONTRIBUTIONS

"Conceptualization, Mihir Amode and Niraj Gavali; methodology, Mihir Amode; software,Niraj Gavali; methodology, Prathemesh Amate, Shraddha Malunjkar, and Niraj Gavali;literature survery,Prathamesh Amate, formal analysis,Niraj Gavali; Result Analysis,Mihir Amode; resources, Prathamesh Amate; dataset working, Niraj Gavali and Mihir Amode; writing—original draft preparation, Mihir Amode; writing—review and editing, Mihir Amode and Shraddha Malunjkar; visualization, Shraddha Malunjkar and Prathamesh Amate; supervision and review , Roshani Raut; project administration, Roshani Raut.

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