IJITCE

ISSN 2347- 3657

International Journal of Information Technology & Computer Engineering

Email : ijitce.editor@gmail.com or editor@ijitce.com

ISSN 2347–3657
Volume 12, Issue 4, 2024

A PROJECT REPORT ON SPOTTING SKIN CANCER USING CNN

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ABSTRACT

Melanoma is a skin cancer which is the most serious type of cancer.It can be treatable by a medical professional. It requires a medical diagnosis. The treatment can be depends on the stage of the disease. So to detect the cancer we are introducing CANCER DETECTION USING CNN. Modern medical image processing techniques work on images captured by the microscope and skin ,then analysed them by using different algorithms and methods. Machinelearning algorithms are being used for processing the images. Manual detection of cancer cell is a tiresome task and involves human error, and computer aided mechanisms are applied to obtain better results as compared with manual detection systems. We have trained a convolutional neural network and obtained a prediction accuracy of 99.8%.

LITERATURE SURVEY

EXISTING SYSTEM

The Existing System of Skin cancer spotting is of complex ways and the accuracy of the systems are not exactly. It only detects some skin diseases. Early research on skin conditionslike melanoma, naevus, and seborrheic keratosis was done utilizing CNN to detect skin cancer. Already existed systems will take time to make an analysis. The number of images indataset are not appropriate in existing systems. It is not an early detection.

ANALYSIS

METHODOLOGY

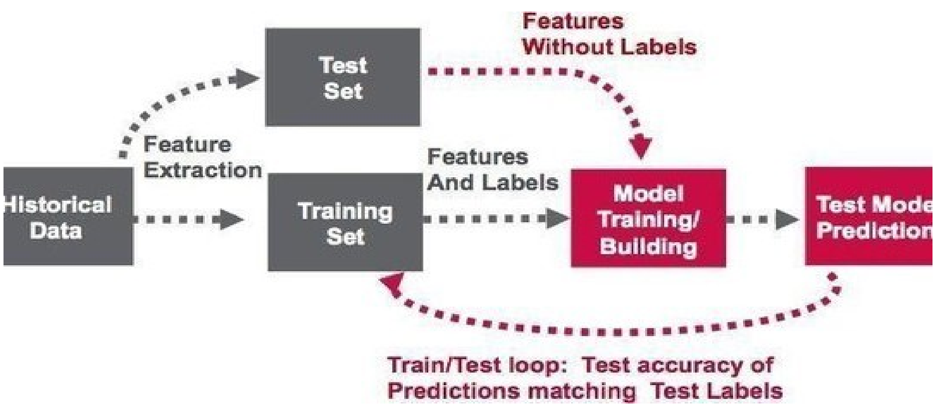

fig:3.1.1 CNN Algorithm

A **Convolutional Neural Network (ConvNet/CNN)** is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various

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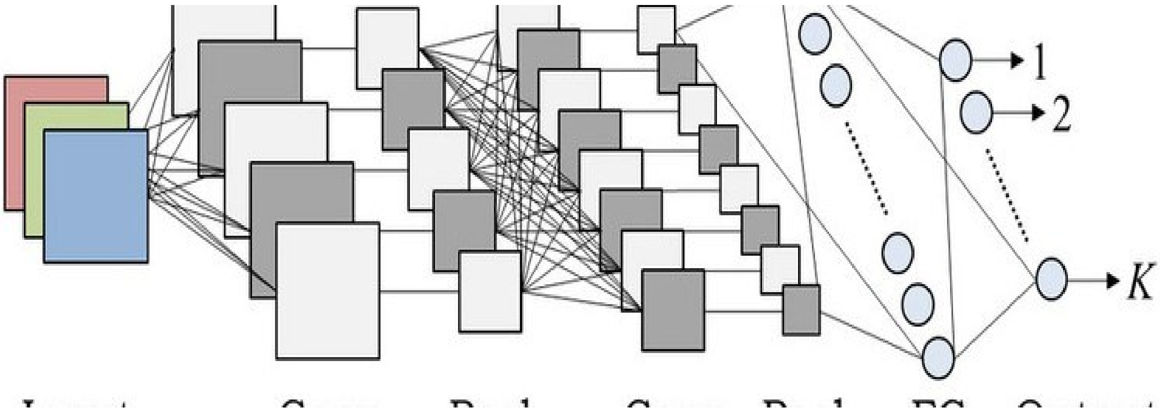
aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.



CONTENT DIAGRAM

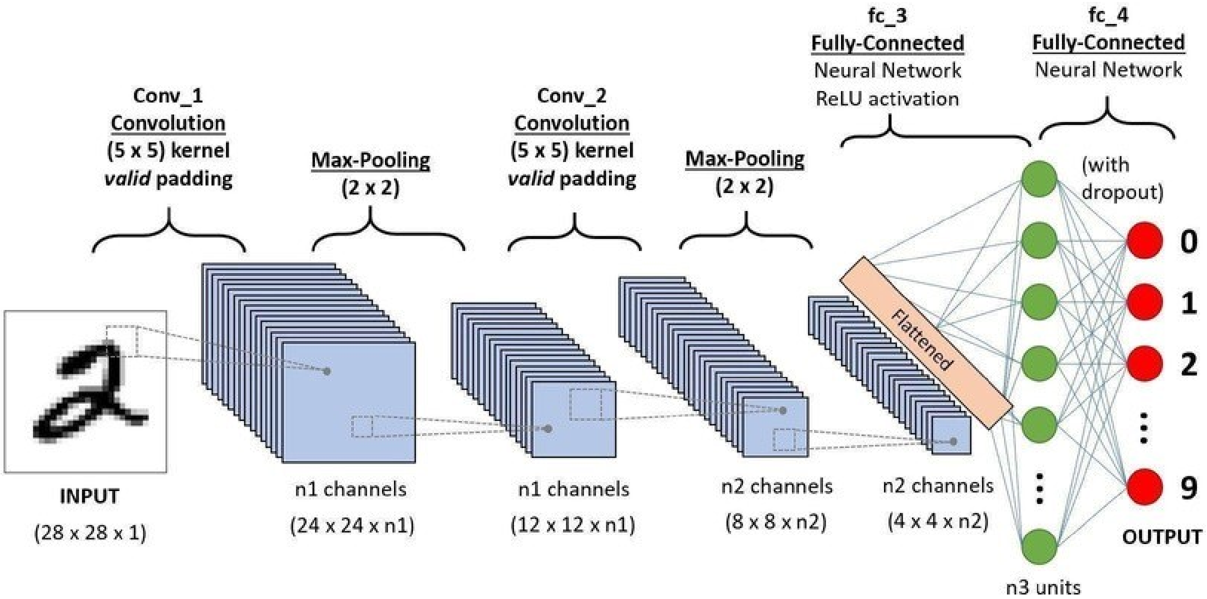


fig:3.2.1 Convolutional neural network architecture

CONVOLUTION PROCESS

An image is nothing but a matrix of pixel values, right? So why not just flatten the image(e.g. 3x3 image matrix into a 9x1 vector) and feed it to a Multi-Level Perceptron for classification purposes? not really. In cases of extremely basic binary images, the method might show an average precision score while performing prediction of classes but would havelittle to no accuracy when it comes to complex images having pixel dependencies throughout. A ConvNet is able to **successfully capture the Spatial and Temporal dependencies** in an imagethrough the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in

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the number of parameters involved and reusability of weights. In other words, the network can be trained to understand the sophistication of the image better

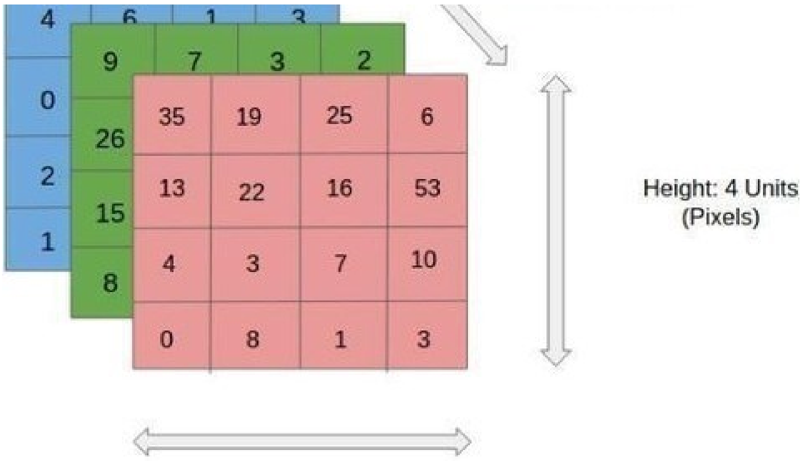

fig:3.2.1 4x4x3 RGB Image

In the figure, we have an RGB image which has been separated by its three-color planes — Red, Green, and Blue. There are a number of such color spaces in which images exist — Grayscale, RGB, HSV, CMYK, etc.

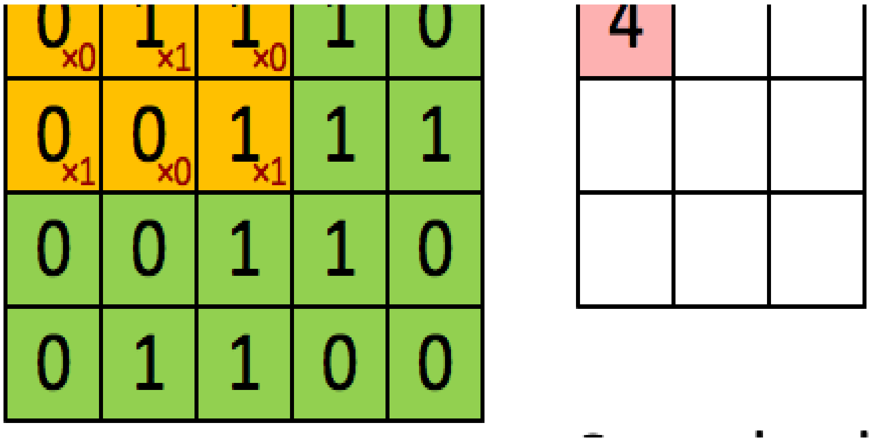

fig:3.5 Convoluting a 5x5x1 image with a 3x3x1 kernel to get a 3x3x1convolved feature.

In the above demonstration, the green section resembles our **5x5x1 input image, I**. The element involved in carrying out the convolution operation in the first part of a Convolutional Layer is called the **Kernel/Filter, K**, represented in the color yellow. We have selected **K as a 3x3x1 matrix.**

Image Dimensions = 5 (Height) x 5 (Breadth) x 1 (Number of channels, eg. RGB)

3.1 KERNEL

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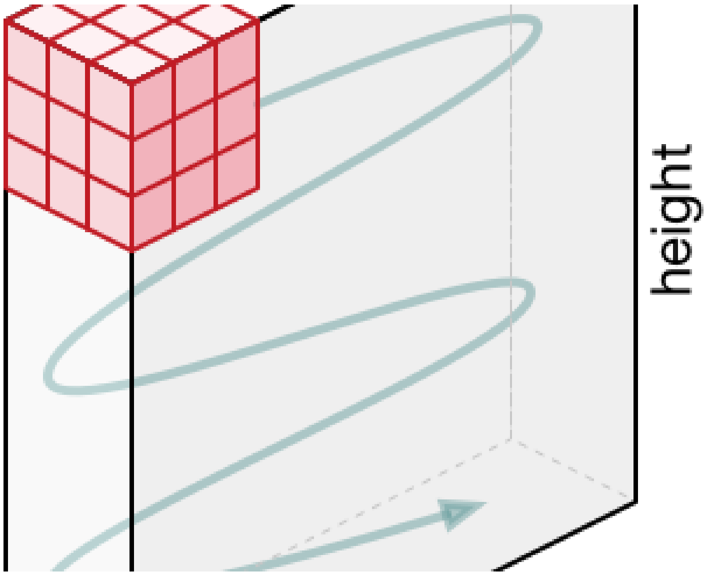

Fig 3.4.1: Movement of Kernel

The Kernel shifts 9 times because of **Stride Length = 1 (Non-Strides)**, every time performing a **matrix multiplication operation between K and the portion P of the image** over which the kernel is hovering

The filter moves to the right with a certain Stride Value till it parses the complete width. Moving on, it hops down to the beginning (left) of the image with the same Stride Value and repeats the process until the entire image is traversed.

3.2 CONVOLU TION OPERATIONS

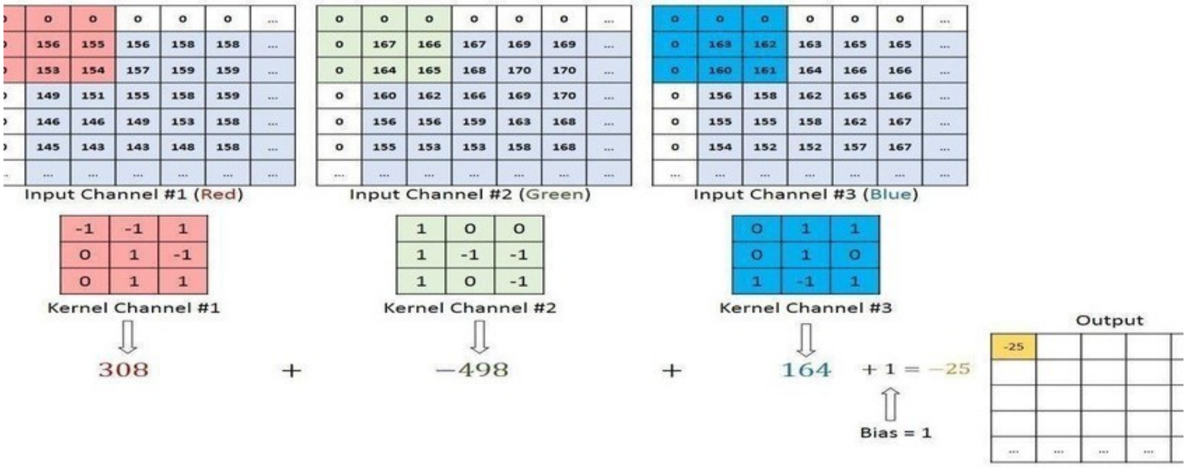

fig 3.5.1 Convolution operation on a MxNx3 image matrix with a 3x3x3 Kernel

In the case of images with multiple channels (e.g. RGB), the Kernel has the same depth asthat of the input image. Matrix Multiplication is performed between Kn and In stack ([K1,I1]; [K2, I2]; [K3, I3]) and all the results are summed with the bias to give us a squashed one-depth channel Convoluted Feature Output.

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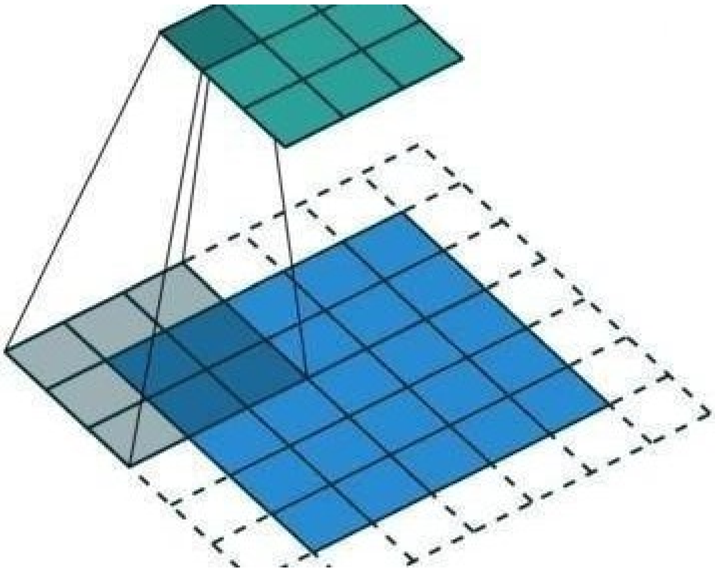

fig 3.5.2 Convolution Operation with Stride Length = 2

The first ConvLayer is responsible for capturing the Low- Level features such as edges, color, gradient orientation, etc. With added layers, the architecture adapts to the High- Level features as well, giving us a network, which has the wholesome understanding of images in the dataset, similar to how we would. There are two types of results to the operation — one in which the convolved feature is reduced in dimensionality as compared to the input, and the other in which the dimensionality is either increased or remains the same. This is done by applying **Valid Padding** in case of the former, or **Same Padding** in the case of thelatter.

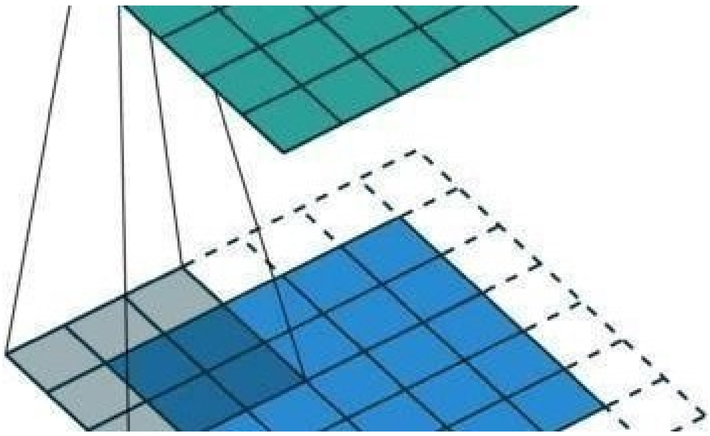

fig 3.5.3 Padding Operation

SAME padding: 5x5x1 image is padded with 0s to create a 6x6x1 image When we augment

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the 5x5x1 image into a 6x6x1 image and then apply the 3x3x1 kernel over it, we find that the convolved matrix turns out to be of dimensions 5x5x1. Hence the name
— Same Padding.

On the other hand, if we perform the same operation without padding, we are presented with a matrix which has dimensions of the Kernel (3x3x1) itself — **Valid Padding**.

The following repository houses many such GIFs which would help you get a better understanding of how Padding and Stride Length work together to achieve results relevant to our needs.

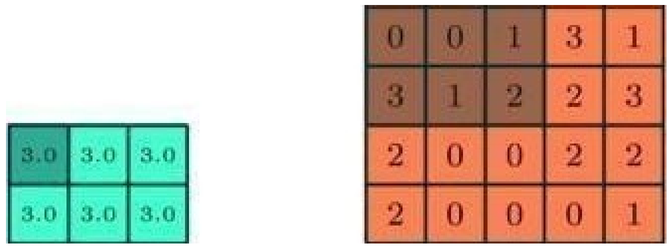
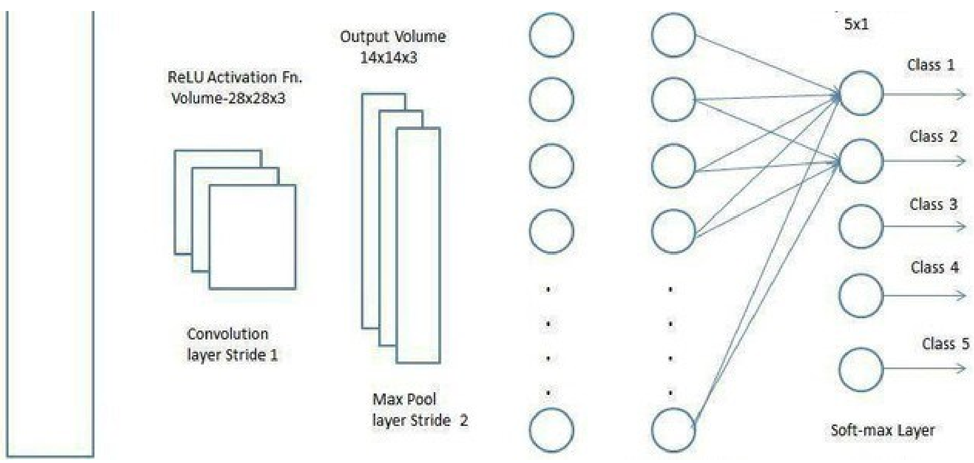


Fig 3.5.4: pooling over 5*5 convolved feature

Similar to the Convolutional Layer, the Pooling layer is responsible for reducing thespatial size of the Convolved Feature. This is to **decrease the computational powe r required to process the data** through dimensionality reduction. Furthermore, it is useful for **extracting dominant features** which are rotational and positional invariant, thus maintaining the process of effectively training of the model.

3.3 Classification — Fully Connected Layer (FC Layer)



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Adding a Fully-Connected layer is a (usually) cheap way of learning non-linear combinations of the high- level features as represented by the output of the convolutional layer. The Fully- Connected layer is learning a possibly non-linear function in that space. Now that we have converted our input image into a suitable form for our Multi-LevelPerceptron, we shall flatten the image into a column vector. The flattened output is fed to afeed-forward neural network and backpropagation applied to every iteration of training.Over a series of epochs, the model is able to distinguish between dominating and certainlow- level features in images and classify them using the **SoftMax Classification** technique

DESIGN

SYSTEM ARCHITECTURE

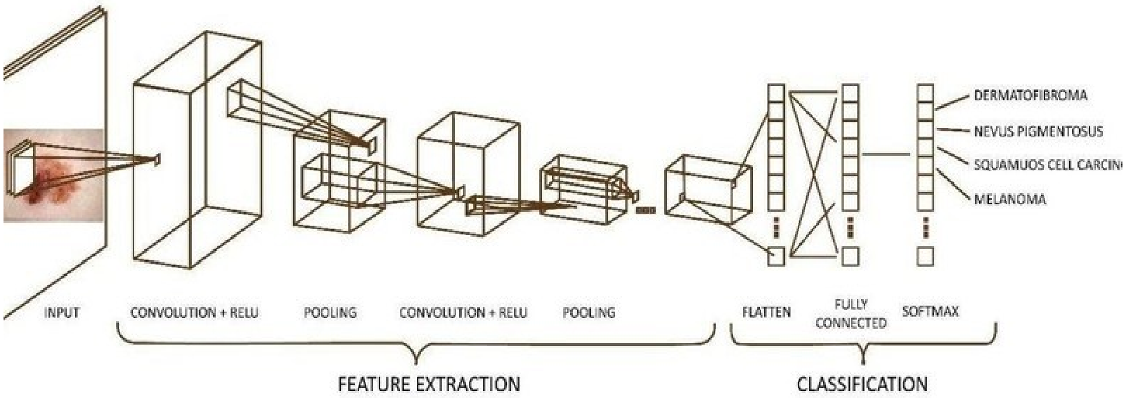

Figure 4.1. Architecture of ConvolutionalLayer

IMPLEMENTATION

:Libraries used:

The libraries used for implementation are:

1. pathlib
2. tensorflow
3. matpotlib.pyplot
4. numpy
5. pandas
6. PIL
7. keras
8. layers
9. Sequential

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1. **Pathlib**:

Pathlib module in Python provides various classes representing file system paths with semantics appropriate for different operating systems. This module comes under Python's standard utility modules.

Path classes in the Pathlib module are divided into pure paths and concrete paths. Pure paths provide only computational operations but does not provides I/O operations, while concrete paths inherit from pure paths and provide computational as well as I/Ooperations.

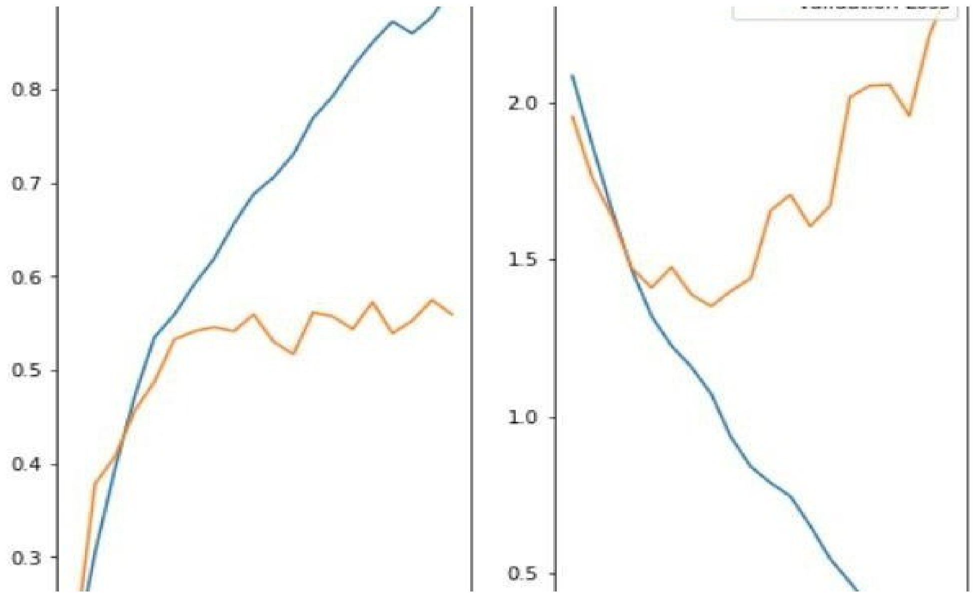
1. **TensorFlow:**

TensorFlow is an open-source software library. **TensorFlow** was originally developed by researchers and engineers working on the Google Brain Team within Google's Machine Intelligence research organization for the purposes of conducting machine learning and deep neural networks research.

TESTING AND VALIDATION

6.1:Output

The specifics of the training and the outcomes will be the ensuing portion. The training data set is divided into two parts: training, which accounts for 80% of the whole data, and testing, which accounts for 20% of the total data.



,Figure 1's validation accuracy and training accuracy differences are rather large, and the loss between the two graphs is also fairly large. This is the final graph that does not include data augmentation.

In the graphic below, the results of the data provided with data augmentation are displayed

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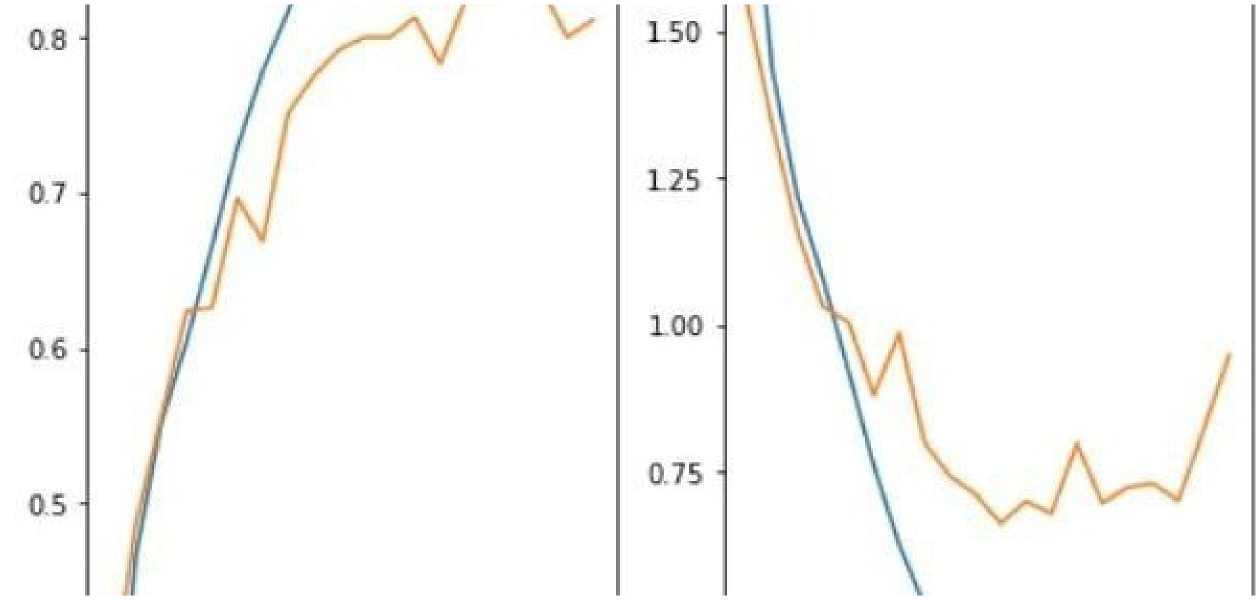

Compared to the earlier results, there is less of a discrepancy between the training and validation accuracy curves in figure-2. There isn't much of a distinction between training loss and validation loss. The outcome in this case establishes definitively that the patient in question has skin cancer, and the medical diagnosis may now be made

Table.1- Performance details about the proposed Model

[redacted]

We can witness a performance comparison of each employed optimizer in Table 1 analysis. The best accuracy and loss performance are provided by this optimizer. Precision, Recall, and F1-Score values are in the range between 0 and 1. The performance parameter values are close to 1,indicating that the CNN model's predicted ability to classify various skin malignancies.

CONCLUSION AND FUTURE SCOPE

Dermatologists would undoubtedly benefit from this skin cancer spotting method, which enables them to distinguish between different types of skin cancer quickly and effectively utilizing commonplace technology like cellphones and laptops. In this case, the procedure is applied using both the original data and the augmented data. The expanded dataset will produce a betteroutcome. The issues with false diagnoses are reduced by this system. It is a quick procedure of enhancing recuperation. Because there would be less human interaction, there will also be less human mistakes.

It has also opened a door to new opportunities for research as there are many undiscoveredareas that can be revealed by techniques and tools of machine learning and deep learning. We may obtain improved results by altering the network design and parameter

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