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Enhancing Skin Cancer Diagnosis with Deep Learning-Based Classification

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Abstract— The diagnosis of skin cancer has been identified as a significant medical challenge in the 21st century due to its complexity, cost, and subjective interpretation. Early diagnosis is critical, especially in fatal cases like melanoma, as it affects the likelihood of successful treatment. Therefore, there is a need for automated methods in early diagnosis, especially with a diverse range of image samples with varying diagnoses. An automated system for dermatological disease recognition through image analysis has been proposed and compared to conventional medical personnel-based detection. This project proposes an automated technique for skin cancer classification using images from the International Skin Imaging Collaboration (ISIC) dataset, incorporating deep learning (DL) techniques that have demonstrated significant advancements in artificial intelligence (AI) research. An automated system that recognizes and classifies skin cancer through deep learning techniques could prove useful in the medical field, as it can accurately detect the presence of skin cancer at an early stage. The ISIC dataset, which includes a vast collection of images of various skin conditions, provides an excellent opportunity to develop and validate deep learning algorithms for skin cancer classification. The proposed technique could have a significant impact on the medical industry by reducing the workload of medical personnel while providing accurate and timely diagnoses..

Keywords- Dermatology, Image Processing, Convolutional neural network (CNN), Deep Learning, SGD Optimizer, Melanoma.

I. INTRODUCTION

The skin is the outermost layer of the human body and serves as a protective barrier against environmental factors such as dust, pollution, microorganisms, and UV radiation. In addition to safeguarding the inner muscles, bones, and tissues, skin-related diseases can result from genetic instability, making them particularly complex. The role of the skin in protecting the body from UV radiation is critical, as exposure to the sun can damage DNA in skin cells and lead to skin-related diseases and various types of skin cancers. Melanin, found in skin cells, acts as a protective measure against UV radiation, with individuals with darker skin tones having more melanin and therefore more protection against UV radiation than individuals with fair skin.

Dermoscopy is a non-invasive evaluation method that allows for the visible study of subsurface structures of the skin using incident light and oil immersion shown in Figure 1. This technique has proven to be more effective in detecting skin cancer than unaided observation-based detection. However, the accuracy of dermoscopy diagnosis relies heavily on the training of the dermatologist. The basic principle of dermoscopy involves the transillumination of a lesion and the use of high magnification to visualize subtle features. The physical characteristics of the epidermis, the top or outer layer of the skin, can impact light occurrences such as reflection, refraction, diffraction, and absorption. Dry, scaly skin is more likely to deflect light, whereas smooth, oily skin is more likely to allow light to travel through it and reach the lower layers. The use of linkage fluids applied over lesions to be studied improves the translucency of the skin and can aid in the visibility of subsurface skin structures.

Figure 1. 4th Generation Dermoscope (dermatoscope)

The human flesh comprises two primary layers, the epidermis and the dermis. The epidermis is composed of three types of cells, including flat and scaly cells on the surface known as squamous cells, round cells known as basal cells, and melanocytes that provide skin its color and protect against skin damage. Melanoma, a particularly deadly form of skin cancer, accounts for only 4% of all skin cancers but is responsible for 75% of all skin cancer deaths. Therefore, an automatic diagnosis tool is crucial for physicians. Although expert dermatologists use dermoscopy for diagnosis, the accuracy of melanoma diagnosis is estimated to be only 75-84%. The Optics of a Dermoscope is shown in Figure 2.

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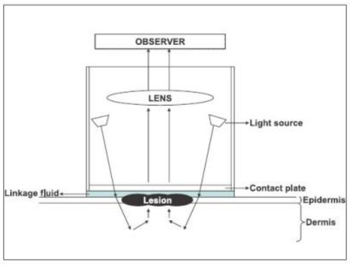

Figure 2. Optics of a Dermoscopy

It affects 125 million people worldwide, which is equivalent to two to three percent of the world's population, according to the International Federation of Psoriasis Associations. Early detection and treatment are essential for healing melanoma, as late detection can result in cancer spreading to other areas of the body and penetrating deeply into the skin. Types of Skin Cancer and their level of penetration are in Figure 3. Computer-aided diagnostics can improve both the quickness and precision of detection, as they can extract information that may not be readily perceived by human eyes, such as color variation, asymmetry, and texture features.

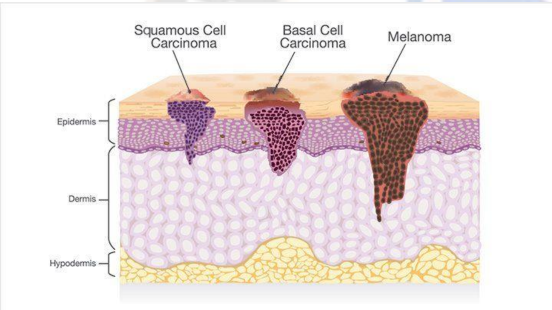

Figure 3. Types of Skin Cancer and their Level of penetration

Numerous methods and formulas, including the ABCD rule, the seven-point checklist, and the Menzies technique, have been suggested to enhance the diagnosis of melanoma skin cancer.

II. LITERATURE REVIEW

In a 2020 study, MA. Ahmed Thaajwer et. al proposed a method for detecting melanoma skin cancer that does not rely on the biopsy method, which can be time-consuming and painful. Instead, they developed a computer-aided screening method using image processing techniques and the Support Vector Machine (SVM) algorithm. However, the researchers found that using a Convolutional Neural Network (CNN) outperformed SVM in terms of testing accuracy. Specifically, when using pixel-based reflectance samples without segmentation size, CNN achieved a significantly higher level of accuracy compared to SVM, with an increase in overall classification performance of approximately 7.7%. Shivangi Jain et al. (2015) described a computer-aided technique for the detection of melanoma skin cancer using image processing tools. This method uses novel image processing techniques to analyze skin lesion images for the presence of cancer. Lesion Image Analysis tools are used for texture, size, and shape analysis to segment the image and identify different Melanoma characteristics such as asymmetry, border, color, and diameter (ABCD). However, the ABCD analysis in this method results in longer processing times compared to the CNN-based system proposed by Thaajwer et al.

William Stolz et al. (2020) noted that dermoscopic, which are commonly used to study melanocytic nevi and melanoma in individuals with white skin, can also be used to diagnose other skin conditions such as psoriasis, lichen planus, and dermatofibroma. However, dermoscopy are expensive and not readily available in developing countries. The potential of dermoscopy for studying inflammatory and pigmentary dermatoses has yet to be fully explored. In a 2019 study, Vijayalakshmi M M et al trained the Back Propagation Algorithm (Neural Networks) and SVM on a dataset collected from the ISIC database. After training, they evaluated the accuracy of the model's outputs. The purpose of the study was to identify a reliable skin cancer prediction method and classify skin cancer as either malignant or non-malignant melanoma. They found that the SVM multiple class classification had an accuracy of 50%, while the CNN-based multiple class classification achieved an accuracy of 75.8%.

Yasmeen George et. al (2020) developed a method for identifying and describing keypoints in skin lesions using superpixels and local feature descriptors, followed by the K-means grouping method to create a codebook. However, Thaajwer et al's CNN-based method achieved better results. Thaajwer et al used the Xception architecture, which includes a 71-layer deep CNN that can classify images into 1000 different categories based on a pre-trained version trained on over a million images from the ImageNet database. Finally, Nadia et al. (2020) proposed a technique for identifying and categorizing skin lesions using dermoscopy pictures based on the ABCD principles. Their approach involves four steps: 1) pre-processing with filtering and contrast-enhancing algorithms; 2) segmentation to identify the tumor; 3) feature extraction to calculate asymmetry, boundary irregularity, color, and diameter; and 4) classification based on the aggregate of the four extracted factors multiplied by their weights. However, their system achieved an accuracy of only 90%, compared to Thaajwer et al's CNN-based system, which achieved an accuracy of 98.4%. Like Jain et al's system, Nadia et al's approach also involve longer processing times due to the use of the ABCD rule.

III. ALGORITHMS

In this work, a skin cancer classification framework based on deep learning by using a pre-trained CNN is proposed.

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A. Tensorflow Keras Optimizers:

The family of optimizers has been extended to include techniques that are used to train deep learning or machine learning models. Optimal optimizers can enhance both the speed and performance of training. During neural network training, the weights are initially set to arbitrary values and then updated in each epoch to improve the network's overall accuracy. This is accomplished by comparing the output of the training data to the actual data using a loss function to calculate the error, after which the weights are updated accordingly.

B. Adam:

The Adam optimizer is a type of optimizer that utilizes the Adam algorithm. This stochastic gradient descent technique involves the adaptive estimation of first- and second-order moments.

C. Stochastic gradient descent (SGD):

Stochastic gradient descent is an iterative approach used for optimizing an objective function that possesses appropriate smoothness characteristics. It can be considered a stochastic version of gradient descent optimization since it utilizes an estimation of the gradient instead of the actual gradient. This results in a reduction of the computational workload, especially for high-dimensional optimization tasks, allowing for faster iterations, albeit with a reduced convergence rate.

D. Xception:

The architecture of the Xception model, which is a 71-layer deep convolutional neural network, was inspired by the Inception model developed by Google, but it is an extreme version that uses depthwise separable convolutional layers.

E. ResNet50:

The ResNet-50 model is a widely-used CNN with 50 layers, belonging to the category of deep residual networks. Residual Neural Networks (ResNets) are a type of Artificial Neural Network (ANNs) that are constructed by stacking residual blocks on top of each other.

CONVOLUTIONAL NEURAL NETWORKS

In the realm of deep learning, CNNs are a type of deep neural network that is frequently used to analyze visual imagery, as illustrated in Figure 4. The ConvNet performs convolution, which is a mathematical process that combines two functions to produce a third function that explains how one shape is altered by the other.

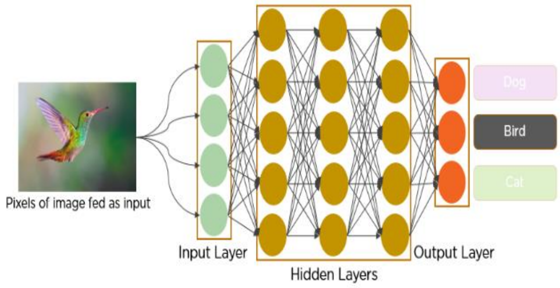

Figure 4. Convolutional network model architecture

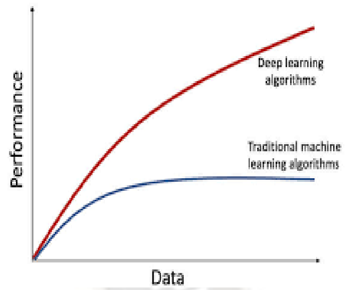

Figure 5. Performance of deep learning over traditional algorithms

CNN plays a significant role in reducing images into a form that is more manageable to process while preserving critical features for accurate prediction. CNNs are particularly useful in image recognition and excel at identifying non-linear correlations among large datasets of images. On the other hand, SVM is margin classifiers that offer various kernels for classification. SVMs may struggle when predicting class labels for vast datasets and are challenging to parallelize. In contrast, the CNN architecture naturally supports parallelization.

IV. PROPOSED WORK

A novel approach for automated skin cancer classification using deep learning techniques and the ISIC dataset images is proposed, which has shown remarkable progress in the artificial intelligence domain. The proposed technique consists of several modules depicted in figure 6:

Module 1 involves providing a dataset of dermoscopic images to the system, which is a type of magnifier used to capture skin lesion pictures.

Module 2 aims to preprocess the input image to improve its quality by removing undesired distortions or enhancing relevant features for further processing and analysis. The image is scaled down to a fixed size and shape with a pre-matched training rate.

Module 3 involves loading the dataset with appropriate optimizers to reduce the loss function of the working model.

Module 4, the model is fitted with the trained dataset based on the specified epochs, steps, and processing power of the system. The model recursively trains on the data and provides accuracy for every computed result.

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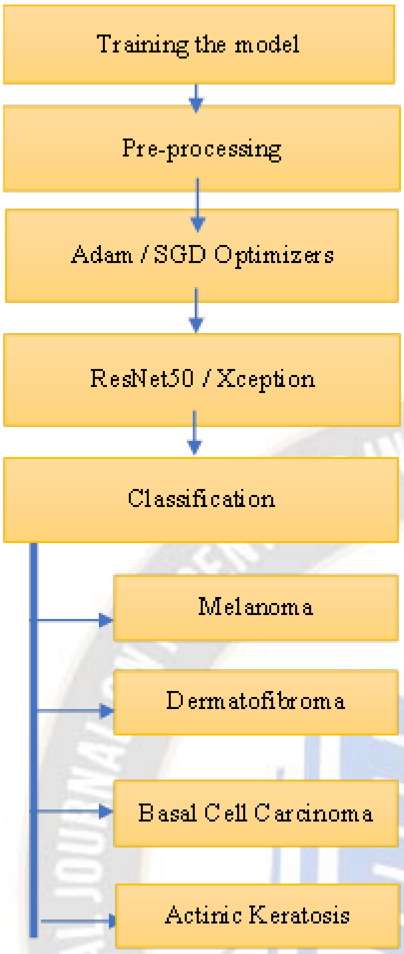

Figure 6. Proposed Methodology

Module 5 involves passing the results, loss function, and accuracy of the saved model to a scaled dermatology image. The model finds the best fit based on the training results and classifies it into pre-determined classes, such as Melanoma, Dermatofibroma, Basal cell carcinoma, and Actinic keratosis.

TYPES OF SKIN CANCER DETECTED

a) Actinic Keratosis

Actinic keratosis (AK) is a skin condition characterized by the development of rough and scaly patches on the skin, which, if left untreated, can progress to squamous cell carcinoma, a form of skin cancer. Sun damage is the leading cause of AK, and the most effective prevention method is to protect oneself from UV light exposure. Failure to seek treatment for AK can result in the development of squamous cell carcinoma.

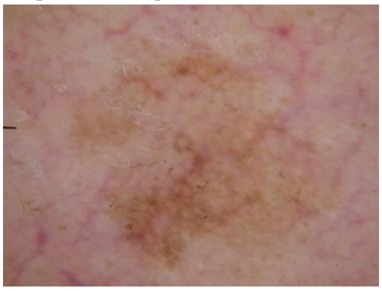

Figure 7. Actinic Keratosis

b) Basal Cell Carcinoma

Basal cell carcinoma (BCC) is a type of non-melanocytic skin cancer that originates from the small, round basal cells located in the lower layer of the epidermis. The prognosis for patients diagnosed with BCC is usually favorable, but if the disease is left untreated, it can lead to significant morbidity. BCC is the most common type of skin cancer and the most prevalent form of cancer overall, with approximately 3.6 million cases diagnosed annually in the United States alone.

Figure 8. Basal cell Carcinoma

c) Dermatofibroma

Dermatofibromas are benign skin growths, also known as papules, that can occur on any part of the body. However, they are typically found on the upper back, arms, and lower legs. They have a dense and firm texture and are often described as feeling like a small stone underneath or raised above the skin. While most dermatofibromas are asymptomatic, some individuals may experience tenderness, irritation, or itching at the site of the growth.

Figure 9. Dermatofibroma

d) Melanoma

Melanoma is a form of skin cancer that, while not the most prevalent, is considered the most severe due to its tendency to metastasize. Once cancer has spread, it can be challenging to manage, and the prognosis may not be favorable. Various risk factors are associated with the development of melanoma, including excessive exposure to the sun, fair skin, and a family history of the disease, among others.

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Figure 10. Melanoma

SOFTWARE USED:

Jupyter Notebook (Python)

- Python is an open-source and interpreted programming language that is dynamic and high-level.
- Object-Oriented programming is one of its key features, including support for classes, objects, and encapsulation.
- Python can create Graphical User Interfaces using modules such as PyQt5, PyQt4, wxPython, or Tk.
- PyQt5 is the most widely used option for creating graphical applications with Python.
- Python provides 2D and 3D graphics functions for data visualization.
- Interactive tools are available for iterative exploration, design, and problem-solving.
- Streamlit is an open-source Python library that simplifies the creation and sharing of custom web applications for machine learning and data science.

SYNTAX:

Loading the Dataset:

Here, we are giving the collected dataset as input from the system. Input to the proposed system is dermoscopic images.

```
training_set = train_datagen.flow_from_directory(
        'Datasets/training',
        target_size = IMAGE_SIZE,
        class_mode = 'categorical',
        batch_size = 16)
```

Initializing Training Method :

When designing a neural network model, it is crucial to consider weight initialization. The nodes within neural networks consist of weights that are utilized to compute a weighted sum of the inputs.

xception = Xception(include_top=False, input_shape = input_shape, weights = 'imagenet')(inputs)

Xception is a deep convolutional neural network architecture that involves Depthwise Separable Convolutions.

res_net = ResNet50(input_tensor = input_tensor, include_top = False, weights = 'imagenet')(inputs)

ResNet is a powerful backbone model that is used very frequently in many computer vision tasks. ResNet uses a skip connection to add the output from an earlier layer to a later layer. This helps it mitigate the vanishing gradient problem.

Set Optimizers :

opt1 = Adam(lr=TRAINING_RATE)

opt2 = SGD(lr=TRAINING_RATE)

Stochastic gradient descent (often abbreviated SGD) is an iterative method for optimizing an objective function with suitable smoothness properties (e.g. differentiable or sub-differentiable).

V. RESULTS AND DISCUSSION

The ISIC skin cancer dataset was utilized to test the proposed system. The dataset comprised 1022 images, which were used to train and test the CNN-based model. Specifically, 113 images were assigned to Actinic Keratosis, 376 to Basal Cell Carcinoma, 95 to Dermatofibroma, and 438 to Melanoma. Both Adam and SGD were employed for training, with images resized to 128x128 pixels and a training rate of 0.0001, and an epoch count of 500 to enhance accuracy. The loss and accuracy were plotted for various epochs, and the results are presented below.

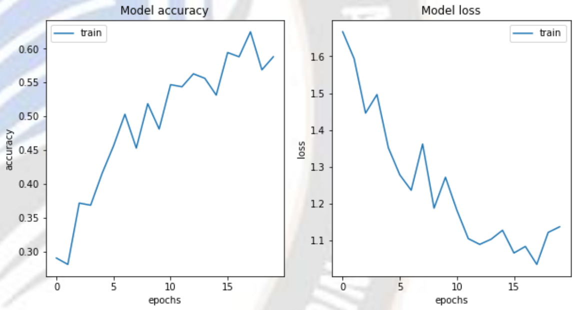

Figure 11. 20 Epochs

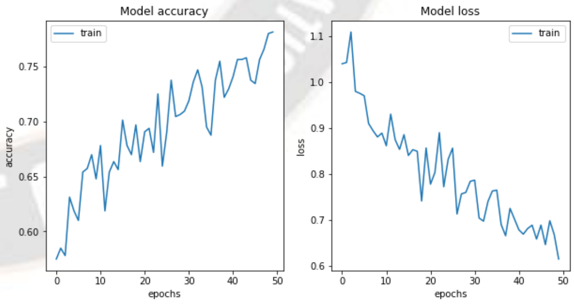

Figure 12. 50 Epochs

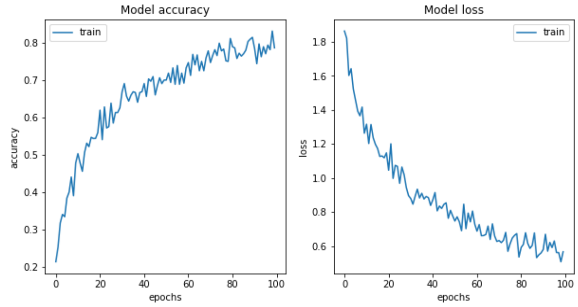

Figure 13. 100 Epochs

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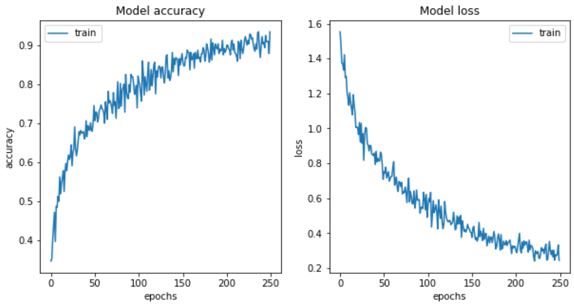

Figure 14. 250 Epochs

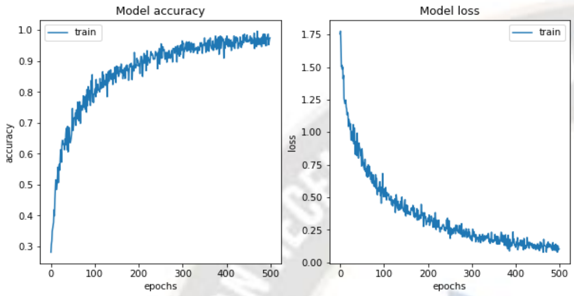

Figure 15. 500 Epochs

The line graphs presented above illustrate the relationship between Accuracy and Losses with varying numbers of epochs. In deep learning and statistics, the learning rate is a significant parameter that determines the step size at each iteration in an optimization algorithm while approaching the minimum of a loss function. To achieve improved accuracy and lower losses, different learning rates were employed during the model training, with a fixed value of 0.0001 yielding the best results overall. The accuracy and loss metrics were computed based on the numbers of true positives, false positives, false negatives, and true negatives.

True Positive (TP) corresponds to a diseased image correctly identified as diseased, while False Positive (FP) denotes a normal image mistakenly classified as diseased. False Negative (FN) refers to a diseased image inaccurately labeled as normal, and True Negative (TN) corresponds to a normal image correctly identified as normal. Accuracy was calculated using the formula (TN+TP)/(TP+FP+FN+TN). The accuracy and losses were found to be (62.1%, 95.7%) for 20 epochs, (79.2%, 62.5%) for 50 epochs, (82.8%, 58.2%) for 100 epochs, (94.1%, 21.6%) for 250 epochs, and (98.4%, 7.7%) for 500 epochs. The model was then integrated into a Python extension named Streamlit, which receives the test image as input, predicts using the model, and returns the image class as one of {‘actinic keratosis', 'basal cell carcinoma', 'dermatofibroma', 'melanoma'}.

Figure 16. Output classified against provided image and displayed in Streamlit

VI. CONCLUSION

This study aimed, to accurately predict and classify skin cancer based on its features using CNN. The loss function of the model was minimized using Adam and SGD Optimizers, and deep neural networks was utilized for classification. The ISIC dataset was employed, and after 500 epochs, the accuracy and losses were measured at (98.4% and 7.7%). The accuracy was found to be directly proportional to the number of epochs, while the loss was inversely proportional to it.

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