CONVOLUTIONAL NEURAL NETWORK FOR DETECTION OF SKIN CANCER

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Abstract: Skin cancer is common and dangerous. This illness, like other cancers, requires early detection. Conventional skin cancer diagnosis methods are inaccurate and can lead to unnecessary inspections. Certain cancer detection machine learning algorithms support a limited number of skin cancer classifications, which might be a drawback. The research method can automatically detect skin cancer and benign tumor lesions using the Convolutional Neural Network. The model contains three hidden layers with 16–32–64 output channels. The model uses SGD, RMSprop, Adam, and Nadam optimizers with a learning rate of 0.001. The Adam optimizer classifies ISIC dataset skin lesions as benign or malignant with 93% accuracy. The results outperform the current skin cancer classification approach. This study uses ISIC [24].
Keyword: Skin Cancer , ISIC , Convolutional Neural Network, Adam, and Nadam.

I. INTRODUCTION

Skin cancer has emerged as one of the malignancies with the quickest rate of progression during the last decade [1]. It makes perfect sense that the skin, which is the largest organ in the body, would also be the organ that is most often afflicted by cancer [2]. Melanoma and nonmelanoma are the two most common forms of cancer that may occur on the skin [3, 4]. Melanoma is a kind of skin cancer that is very hazardous, difficult to diagnose, and, in the end, always deadly. According to research conducted and published by the American Cancer Society [4,] despite the fact that melanoma skin cancer accounts for just 1% of all cases, it has a higher death rate. Melanocytes are the cells that melanoma most often attacks when it does so. The first reason is an aberrant proliferation of melanocytes that are otherwise operating correctly. It does not matter what portion of a person's body you target. Hands, face, neck, lips, etc. are frequent sites for its emergence owing to regular sun exposure. Melanoma is a kind of cancer that can only be cured if it is discovered at an early stage; otherwise, it will metastasis and lead to a horrible death [5]. Nodular melanoma, superficial spreading melanoma, acral lentiginous, and lentigo maligna are all subtypes of melanoma skin cancer [3]. Cancers of the non-melanomous cells, including basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and sebaceous gland carcinoma, are responsible for the great majority of all cancer diagnoses. Basal cell carcinoma (BCC) is the most common form of non-melanoma skin cancer (SGC). The middle and higher layers of the epidermis are where the development of basal cell carcinoma, squamous cell carcinoma, and squamous follicle carcinoma all take place. These cancer cells have a slim chance of metastasizing, which is the term used to describe the process by which cancer spreads to other organs. Cancers that are not melanoma are much easier to treat than those that are caused by melanoma tumors.

Due to their prolonged time spent in the sun, women are more likely to get skin cancer on their heads, faces, lips, ears, necks, chests, arms, hands, and legs. Men are more likely to develop skin cancer on their hands and feet. On the other hand, it is also possible for HPV to show up in locations that are undetectable, such as the palms of your hands, the gaps between your fingers and toes, and the vaginal region..

Anyone may get skin cancer, not only those with lighter skin. Melanoma is more common in parts of the body that are seldom exposed to sunlight, such as the palms and soles, among persons with darker skin tones.

1.1 Symptoms of basal cell carcinoma

- Sun-exposed parts of the body, such the face and neck, are common sites for basal cell carcinoma.
- Symptoms of basal cell carcinoma include but are not limited to the following:
- Definition: a lump that is pearly or waxy
- It's a flat, scar-like lesion that may be either flesh-colored or brown.
- A wound that bleeds or scabs over, only to reopen

1.2 Symptoms of squamous cell carcinoma

Squamous cell carcinoma is most common on regions of the body that are often exposed to the sun, including the face, ears, and hands. Squamous cell carcinoma is more common in those with darker skin in parts of the body that are seldom exposed to sunlight.

- The following are some of the possible manifestations of squamous cell carcinoma:
- A hard, crimson bump
- A scaly, crusty, and superficial lesion

1.3 Symptoms and indicators of melanoma

Melanoma may manifest itself on any area of the body, either as a new growth or as a change in a preexisting mole that has taken on a malignant appearance. Melanomas of the face and trunk are the most prevalent types to occur in men who have this condition. Carcinoma of this kind often first shows its symptoms in the lower legs of female patients. Melanoma may form on nevus (previously pristine skin) in both sexes, even if the skin has never been exposed to the sun. This is because nevus are precancerous lesions.

Individuals of all skin tones are susceptible to developing melanoma. Melanoma is more common in those with darker skin tones, and it most often appears on the palms, soles, and beneath the fingernails and toenails.

1.4 Symptoms of melanoma include

- Spots of darker coloration spread over a brown background.
- Symptoms such as these may indicate that a mole is cancerous:
- A tiny lesion whose borders aren't smooth and whose color varies from red to pink to white to blue to black
- An itchy or burning sore that causes considerable discomfort
- Spots or dark patches on the palms, soles, fingers, or toes; or on the lips, tongue, gums, lining of the nose, vagina, or anus

1.5 Symptoms and signs of rare skin malignancies

Some other, less prevalent forms of skin cancer are:

- The cancer known as Kaposi's sarcoma. This uncommon kind of cancer begins in the blood vessels of the skin, resulting in discolored patches of skin or mucous membranes.
- People with compromised immune systems, such as those with AIDS or those using drugs that reduce their natural defenses, including those who have received organ transplants, are more likely to develop kaposi sarcoma.
- Kaposi sarcoma is also more common in elderly males of Italian or Eastern European Jewish ancestry, as well as in young men in Africa.
- Celluar sarcoma of the Merkel gland. Hard, glossy nodules may form on or just under the epidermis, or even in hair follicles, due to Merkel cell cancer. Most cases of Merkel cell carcinoma manifest in these anatomical sites: head, neck, and trunk.

This is a cancer of the sebaceous gland. The skin's oil glands are the unlikely yet aggressive genesis of this malignancy. The eyelid is a common site for the development of sebaceous gland carcinomas, which manifest as hard, painless nodules and are sometimes misdiagnosed as being caused by something else.

II. LITRACTURE REVIEW

Comparisons are made between the VGG-16, VGG-19, and a CNN model that was constructed specifically for this purpose. Given that there is a disparity in the depths of the three models, we also studied how the presence of such a difference impacts the performance of a model in the setting of the dataset that we used. The outcomes of the testing indicate that the VGG-19 model is the most accurate one. It received a score of 0.9290 for accuracy and a loss of 1.2842, which demonstrates that it is a reliable instrument that may aid in the diagnosis of skin cancer [9].

It is possible to rapidly build experience in the art of diagnosis by first being familiar with the probability of particular skin illnesses and then comparing this knowledge with the differential diagnostic information received from the visiting staff while working in the clinic [10].

We apply a number of different classification techniques in order to forecast the classifications, and these algorithms make use of information that are obtained from the lesion's numerous qualities, such as its color, texture, and structure. The results of the trial are generally promising [11]. [Note:

Prior research has shown that using image classification to classify the different types of skin cancer is effective. Our approach uses CNN (Convolutional neural network) to recognize and differentiate skin cancer photos from rash images, and then classifies them appropriately. When identifying photos as either skin cancer affected images or rashes images, the model attained an average accuracy of 80.2% over 20 epochs [12].

Deep learning architectures ResNet-101 and Inception-v3 are being used here for the classification job that is being done. The data that were obtained have been analyzed, and the results show that the ResNet-101 architecture has an accuracy rate of 84.09%, while the Inception-v3 design has an accuracy rate of 87.42% [13].

The probe is guaranteed to operate for all persons and body regions, regardless of the moisture status or thickness of the skin on which it is used. Realization and verification of the design were accomplished via the use of full-wave numerical simulations run in CST Microwave Studio [14].

As a result of this, the prescribed dosage was administered uniformly to the affected region, as evidenced by the flatness of the 2D isodose curves and the 3D isodose surfaces at the desired distances from the plane of the active sites inside the applicator [15]. This was demonstrated by the fact that the afflicted region received the correct amount of medication.

The gadget that was proposed has a lateral sensitivity of 0.2 millimeters and can detect things at a depth of 0.55 millimeters. The probe was designed in CST Microwave Studio, created in a phantom of human skin, and validated by measurements [16]. [C]ST Microwave Studio was used.

By entering in their symptoms, users also have the option of being connected with a real doctor. In addition, the user's test history may be seen in the personal section, and the user can ask an expert for advice on a particular test depending on the diagnostic results of the skin condition [17].

The Convolutional Neural Network (CNN) and the Recurrent Neural Network (RNN) are two of the most widely used deep learning classification algorithms. The objective of this poster is to investigate and contrast these two algorithms, as well as to put them through their paces by testing them on large data sets retrieved from the International Skin Imaging Collaboration (ISIC) archive. In addition, the raw datasets provided by ISIC will be preprocessed and scaled before being made available for use in algorithms. In addition, the performance of these approaches will be evaluated and compared using a total of five metrics, one of which is called ROC [18].

As a consequence of our work, we discovered that a Raspberry Pi can be used to power demanding computations such as deep learning, and that this tremendous processing capacity can then be combined into a cheap portable device that can be used for screening [19]. This was a significant discovery for us.

It's possible that mathematical and computational models of skin epidermis modulation in both normal and malignant stages might help with early identification, disease prevention, and treatment plan selection [20].

In addition to this, it has been shown that the values of millimeter-wave reflectivity are much higher for malignant areas in comparison to healthy parts. It is possible to perform MMWI fast because it does not need the processing or staining of tissue. This makes it possible to identify cancers at an early stage and reduces the complexity of the surgery to remove the tumor to a single-layer excision approach [21].

This is a model of reinforcement learning, in which both models get rewards or penalties based on how well they perform. In order to train the discriminator, we make use of clinical measures taken from patients who have skin cancer. The objective of this study is to design a generator that might be put to use to enhance the picture-taking capabilities of hyperspectral imaging techniques used to study skin cancer [22].

III. PROPOSED METHODS

Thus, identification at an early stage is essential for the treatment of skin cancer [23]. A biopsy of the affected area of skin is often performed as the first step in the diagnostic process for skin cancer. The goal of this therapy is to get a tissue sample from a potentially cancerous skin lesion for the purpose of additional medical study in order to determine whether or not the lesion is cancerous. This is a challenging, time-consuming process that moves at a glacial pace. Using a computer to make a diagnosis of skin cancer is not only rapid and easy, but also very affordable. It is possible to determine if the symptoms of skin cancer are brought on by melanoma or another kind of skin cancer using any one of a number of noninvasive diagnostic techniques. A common approach for detecting skin cancer may be broken down into the following phases, which are shown in Figure 1: getting the picture, doing some preprocessing on it, segmenting the image that has been preprocessed, determining the necessary feature, and then categorizing it.
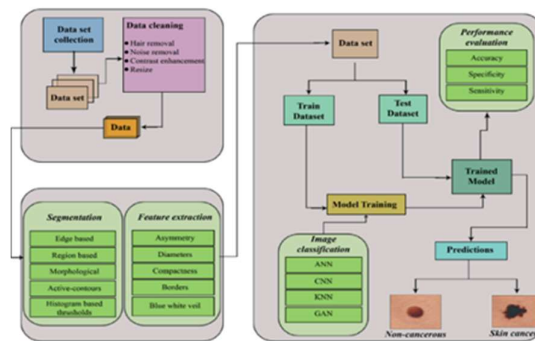

Figure 1: Proposed process diagram.

Table 1. Specifics on the Proposed Model for CNN

Layer (type)	Output Shape	Parameter
Input Image	128,128,3	0
Convolution	128,128,16	448
ReLU	128,128,16	0
Max-Pooling	64,64,16	0
Convolution	64,64,32	4640
ReLU	64,64,32	0
Max Pooling	32,32,32	0
Convolution	32,32,64	18496
ReLU	32,32,64	0
Max Pooling	16,16,64	0
Dropout	16,16,64	0
Flatten	16384	0
Dense	4	65540
Softmax	4	0

Table 1's skin pictures are reduced to 128 pixels by 128 pixels so the 3-hidden-layer CNN model may utilize them. Each of the hidden layers includes filters that alter the image in a 3x3 grid, with 16, 32, or 64 output channels. Each layer's activation uses Rel-U and Max pooling. Table 1 show how Maxpooling reduces image size. Flattening decreases picture depth to one dimension. The softmax activation function will be used to classify skin image conditions as benign or malignant.

Deep learning is widely used in the area of medical imaging, and one of its most common applications is the detection of skin cancer using convolutional neural networks (CNNs). Using CNNs, the following is an algorithm at a high level for identifying skin cancer:

- Gather a huge collection of photos of skin lesions, including both benign and malignant examples, and label each image to indicate whether it depicts a benign or malignant lesion.
- Do any necessary preprocessing on the photos to verify that they are all the same size and are oriented in the same manner. Depending on the circumstances, this may require scaling, cropping, and rotating the photographs.
- Create a training set, a validation set, and a test set out of the dataset. The convolutional neural network (CNN) is trained using the training set, the validation set is used to modify the hyperparameters of the CNN, and the test set is used to assess how well the CNN performs on data that it has not previously seen.
- Explain how CNN's infrastructure works. Convolutional layers, followed by pooling layers, and ultimately fully connected layers that output the classification result would make up the conventional architecture of a CNN designed to detect skin cancer. The difficulty of the issue and the size of the dataset both have a role in determining the number of levels, as do the particular characteristics of each layer.
- Train the CNN on the training set by making use of backpropagation to fine-tune the network's weights in order to get the best possible loss function performance.
- Do an evaluation of the CNN's performance on the validation set, and then make any required adjustments to the hyperparameters (such as the learning rate, the batch size, and the regularization) in order to increase performance.
- Evaluate the performance of the CNN on the test set in order to acquire a definitive assessment of its overall performance after it has been determined that the performance on the validation set is adequate.
- If the performance of the CNN on the test set is good, it may be deployed for use in determining whether or not fresh photos include evidence of skin cancer.
- Lastly, the CNN's performance may be further enhanced by doing fine-tuning on newly acquired data or by using transfer learning from a previously trained CNN to perform a job that is analogous to the original one.

A Convolutional Neural Network (CNN) designed to detect skin cancer would typically have an architecture that is composed of numerous layers, each of which serves a distinct purpose.

The following is an example of a functional architecture for the diagnosis of skin cancer using CNNs:

- Input Layer: This layer usually takes the form of a matrix of pixel values and is responsible for receiving the skin picture as its input.
- Convolutional Layers: These layers execute convolution operations on the input picture by using a series of learnable filters in order to accomplish the task. Each filter isolates a particular characteristic of the picture that it is applied to, such as the image's borders, lines, or textures. The output of this layer is a collection of feature maps, which reflect the learnt features at various spatial places in the input picture. These feature maps may then be used to make predictions about the input image.
- This layer adds a non-linear component to the model by applying a rectified linear activation function to the output of the convolutional layer. This causes the model to behave in a way that is not linear.
- Pooling Layers: These layers downsample the feature maps in order to minimize their spatial size. Depending on the situation, they may use either maximum pooling or average pooling. The computational difficulty of the model is simplified as a result, and the risk of overfitting is mitigated.
- Dropout Layer: Throughout the training process, this layer will, at random, remove some of the neurons that were in the layer below it. This helps to prevent the model from being too accurate.
- Completely Connected Layers: These layers take the output that has been flattened from the layer that came before them and then carry out a series of matrix multiplications in order to generate the final result. This layer will provide a probability distribution as its output, which will indicate the likelihood of each class given the input picture. This distribution will cover all of the possible classes.
- The output layer is responsible for producing the final classification result depending on the output of the layer that came before it. A softmax activation function is commonly used for this layer.
- The architecture described above may be iterated on several occasions to produce a deep CNN with a large number of layers, depending on the size of the dataset.

// Define the CNN architecture
ConvolutionalLayer(filters=32, kernel_size=(3, 3), activation='relu', input_shape=(224, 224, 3))
MaxPoolingLayer(pool_size=(2, 2))
ConvolutionalLayer(filters=64, kernel_size=(3, 3), activation='relu')
MaxPoolingLayer(pool_size=(2, 2))
ConvolutionalLayer(filters=128, kernel_size=(3, 3), activation='relu')
MaxPoolingLayer(pool_size=(2, 2))
FlattenLayer()
DenseLayer(units=512, activation='relu')
DropoutLayer(rate=0.5)

OutputLayer(units=2, activation='softmax')

```
// Define the loss function and optimizer
loss = 'categorical_crossentropy'
optimizer = 'adam'

// Compile the model
model.compile(loss=loss, optimizer=optimizer, metrics=['accuracy'])

// Train the model
model.fit(x_train, y_train, epochs=10, batch_size=32, validation_data=(x_val, y_val))

// Evaluate the model on the test set
test_loss, test_accuracy = model.evaluate(x_test, y_test)

// Make predictions on new data
predictions = model.predict(new_data)
```

IV. RESULTS AND DISCUSSION

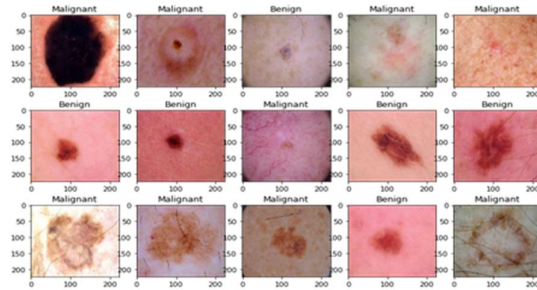In this section explain about skin cancer illistrative example with result related proposed work.

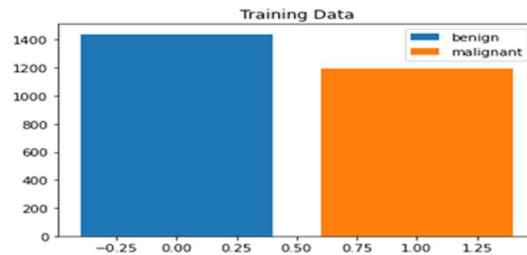Figure 2: Illistrative example of skin cancer.

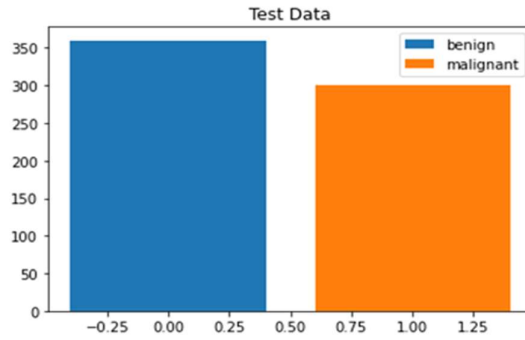Figure 3: Shows bening and malignant data during training data

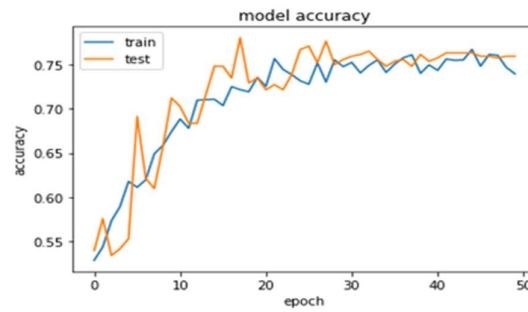Figure 4: Shows bening and malignant data during test data
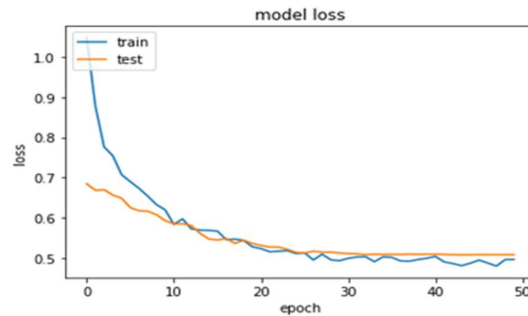

Figure 5: Shows model accuracy.
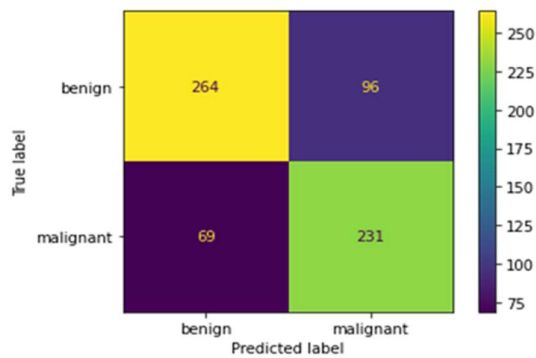

Figure 6: Shows model loss.

Figure 6: Shows confusion matrix of proposed work.

V. CONCLUSION

The use of digital image processing allowed for the development of an automatic system for distinguishing dermatofibroma, nevus pigmentosus, squamous cell carcinoma, and melanoma from one another. The model of a convolutional neural network (CNN) that was used in this investigation contains three hidden layers. Each of these layers has a filter size of three, and they sequentially provide 16, 32, and 64 channel outputs. In addition to that, it has a layer that is completely linked, softmax activation, and a total of 64 input channels. In order to optimize the recommended model, SGD, RMSprop, Adam, and Nadam are all used. The suggested CNN model with Adam optimizer achieved 93% accuracy, loss of 0.4965, and the value of precision, recall, making it the most effective method for differentiating between benign tumor lesions and skin cancer in the dataset. The dataset contains lesions that could be either cancerous or benign.

Declarations :
Ethical approval
This manuscript does not contain any studies with human participants or animals performed by any of the authors.

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Conflict of interest
The authors of this manuscript declare that they have no conflict of interest.

Informed Consent
The research papers which are used for the study of the submitted work have been cited in the manuscript and the details of the same have been included in the reference section.

Competing interests
Not always applicable and includes interests of not a financial or personal nature

Availability of data and materials
Availability as per request

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