Fined Tuned Multi-Level Skin Cancer Classification Model by Using Convolutional Neural Network in Machine Learning

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Abstract- There are thousands of skin cancer patients are registered globally every year. Skin cancer is one of the types of cancer that kills millions of people each year. Early detection and treatment of new dangerous skin cancer cases are critical to ensuring a low death rate as well as a high survival rate. The vast majority of relevant research focuses on machine learning-based algorithms. Another powerful deep learning approach for extracting many properties from an image is a convolutional neural network (CNN). There are two types of images: benign (non-cancerous) and malignant (cancerous) (cancerous). ISIC dataset contains the total number of 2637 images in trained and 660 in the testing dataset used for melanoma detection and classification with the optimum accuracy of 96%.

Index Terms- CNN, testing, training, benign, malignant, skin cancer, melanoma, cancerous, non-cancerous.

I. INTRODUCTION

Skin cancer is on the rise these days. This kind of melanoma and non-melanoma skin cancer (NMSC) is becoming more common in Australia, Spain, Brazil, and other parts of the world, and the major cause is ultraviolet light exposure (UV). The major cause of skin cancer is ultraviolet exposure. Increased exposure to UV radiation has resulted from changes in lifestyle in recent decades; this phenomenon, together with population aging, raises the risk of skin cancer [1].

Deep Learning algorithms are intended to simulate the operation of the human cerebral cortex. These algorithms employ deep neural network representations or neural networks with multiple hidden layers. CNN is capable of training massive datasets with millions of parameters using 2D images as input and filtering to produce the desired results. In this article, CNN models were developed to evaluate their performance in image recognition and detection datasets. The MNIST and CIFAR-10 datasets are used to assess the algorithm's performance [2].

Every year, millions of individuals are affected by skin cancer, which is one of the most severe kinds of cancer. Skin cancer detection in its early stages is an expensive and complicated process. ML-based algorithms have recently been shown to aid dermatologists in classifying medical images in recent studies. By employing the notion of a deep CNN, this research recommends a deep learning model for detecting and classifying skin cancer (CNN). We initially gathered a dataset comprising four skin classes actually before using augmentation techniques to enhance the volume of the resulting dataset. The proposed model achieves 95.98 percent accuracy on the test data, outperforming the two "pre-train models", Google Net reveals an accuracy of 1.76 percent and Mobile Net with 1.12 percent respectively. [3].

A CNN [4] is used to improve prediction accuracy, and a suitable architecture for predicting forest fire susceptibility was designed by hyperparameters along with optimization parameters. The trained algorithm was fed the test dataset to generate a spatial prediction map of forest fire susceptibility in "Yunnan Province." Finally, the proposed model's predictive ability was evaluated using a variety of statistical metrics, such as the "Wilcoxon signed-rank test," receiver operating characteristic curve, and area under the curve (AUC). CNN incorporates the HAM10000 dataset (a massive collection of diverse sources of dermatoscopic common colored skin lesion images) (CNN). The algorithm produces the three most likely diagnoses of dermatitis and informs us if a lesion is malignant or non-cancerous. The model's hyper-parameter tuning is then employed to further enhance the deep learning approach [5].

A unique hierarchical multi-label classifier is created by combining all of the hierarchically organized local classifiers into a single DCNN model with multiple heads and ends (MHME). The three sections of the MHME CNN technique are as follows: Multiple local classifiers use a DCNN model for feature mapping and extraction. A multi-head component of a collection of linear multi-label classifiers [6], and a multi-end component of a set of auto-encoders that accomplish feature fusion by changing the input vectors of distinct local classifiers into feature vectors of the same length to share the feature mapping portion.

Densenet201 to fine-tune and train a pre-trained deep learning model, a deep learning model on imbalanced data is used. The characteristics of the trained model are derived from the average pool layer, which contains extremely detailed information about each malignant tumor. However, feature selection methodologies are presented because specific layer parameters alone are insufficient for accurate classification. The primary methodology is "Entropy–Kurtosis"-based High Feature Values (EKbHFV), while the second methodology is a metaheuristic-based improved genetic algorithm (MGA). The proposed new threshold function refines the GA's chosen attributes even further. Finally, using a multiclass SVM cubic classifier and a non-redundant serial-based methodology, both EKbHFV and MGA-based features are merged and classified [7].

II. SKIN CANCER ISIC DATASET

A. Dermato-Fibroma

Benign tumors are formed by an expansion of a variety of cells in the skin's dermis layer. Dermato-fibroma develops after mild skin damage; such as gashes from glass splinters or insect bites. Dermato-fibromas have a diameter of 2-3 mm, are purplish brown, have a rigid structure, and are unpleasant to contact. [8].

B. Carcinoma Of Squamous Cells

Squamous Cell Carcinoma is a kind of cancer that affects the skin. A carcinoma is a form of skin cancer that affects the body's exposed parts, such as the legs, arms, lips, ears, face, neck, and head. This kind of skin cancer is not as harmful as others. [9]. If found early enough, this sickness advances slowly and can be properly treated non-surgically. Because of the delay in treatment, the benign tumour may grow to malignancy and spread to bones, tissues, and even lymph nodes. The more widespread cancer, the more difficult it is to treat.

C. Melanoma

This is a very serious kind of skin cancer. This illness develops on the human skin and has the potential to migrate to other organs. Melanocyte cells, which produce melanin in the skin, are responsible for the development of this kind of skin cancer. Melanoma may be identified by its irregular form and the presence of numerous hues. Melanoma-affected moles may be itchy and bleed, and they may be bigger than typical moles [10].

Figure 1. ISIC Dataset [11]

III. RELATED WORK

Our key challenge is melanoma screening to identify skin cancer in a short time since skin cancer melanoma is rapidly expanding internationally every year [12].

The hybrid CNN proposed includes three separate feature extractor segments that are blended to provide more detailed lesion feature maps. Multiple fully connected layers are employed to identify single and fused feature maps, and an ensemble is used to forecast a lesion class. Lesion segmentation, augmentation (geometry and intensity-based), and class rebalancing are among preprocessing approaches (penalizing the loss of the majority class and merging additional images with the minority classes) [13].

Fine-tuning parameters are used to increase model accuracy, and after fine-tuning, the accuracy gain could have been raised. With the help of fine-tuning, we can update the parameters' accuracy [14]. We can make small changes with fine-tuning in deep learning to increase accuracy.

Evaluate the chance of a DL algorithm [15], CNN is a type of neural network used to detect skin cancer by categorizing benign and malignant moles. Recent research used various deep learning models on real-world datasets to construct classification algorithms. The dataset used for this study is ISIC, which has 2460 colored images in total. The training set consists of 1800 images, whereas the testing set comprises 660. A full procedure for establishing and operating the system is also provided. To build our model, we employed Keras and TensorFlow. With some tuning to the parameters and classification methods, our suggested VGG-16 model looks promising. The accuracy of the model is 87.6 percent.

The CNN method [16] it's also utilized to get more information out of test and training datasets. The classification model is designed using this two-feature vector. This classifier determines if the dermoscopy images show melanoma or non-melanoma skin cancer. The suggested approach was tested on two common datasets and found to be more effective than earlier machine learning methods, with an accuracy of 99.85%, sensitivity of 91.65%, and specificity of 95.70%.

Three distinct feature extractor segments are merged to create more comprehensive lesion feature maps in the hybrid-CNN suggested. Multiple fully connected layers are employed to identify single and fused feature maps, and then an ensemble is used to forecast a lesion class. Preprocessing techniques include lesion segmentation, augmentation (geometry and intensity-based), and class rebalancing (penalizing the loss of the majority class and merging additional images with the minority classes).

This study relied on the ISIC dataset [17], to identify skin cancer by distinguishing between benign and malignant cancerous cells for this purpose, a diagnostic model based on CNN, GA, and PSO was developed. The EfficientNetB0 CNN model, which has an accuracy rating of 86.25 percent, was used to train the data set at first. After that, the GA-based feature selection approach was used to improve the performance outcomes, resulting in an average accuracy of 90.09 percent. In addition to the feature selection technique, the PSO algorithm was used as an optimization strategy. When the characteristics selected using this strategy were classified using the SVM method, an accuracy rating of 87.77 percent was obtained. A classification accuracy rate of 89.08 was achieved utilizing both optimization approaches and a feature set consisting of common and specifically specified properties.

IV. IM METHODOLOGY

A. Data Acquisition

Despite the availability of various datasets of dermoscopic images, identifying malignant skin infections remains a difficult problem that necessitates enormous quantities of data to Test and train appropriate models. As a result, only a few datasets have enough pictures to train machine learning (ML) and deep learning (DL) models for skin lesion detection and classification

[18]. We used a dataset that was made accessible to the public in this study. The dataset was contributed by the ISIC Archive. [19]. "Skin cancer" is the most rapidly spread disease around the globe which affects men and women of every skin color [20]. We have tested and trained a dataset with CNN (Convolutional Neural Network) algorithm that followed many steps to conduct the experimental phase. Initial detection of skin cancer stands very significant before it becomes a melanoma dangerous type we have selected CNN to detect melanoma[21].

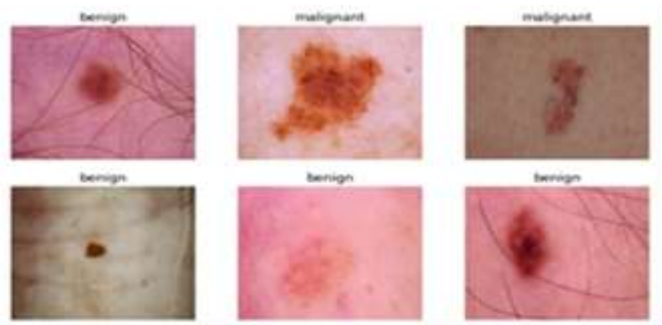

Figure 2. Benign Images

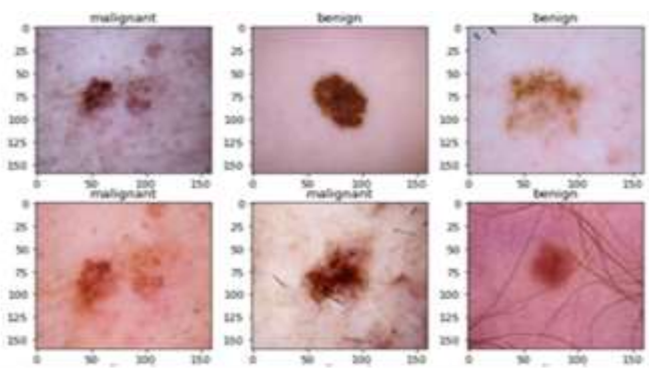

Figure 3. Malignant Images

B. Convolution

The concept of convolution is often used in convolution neural networks. It's a relatively new and popular approach [22]. The input matrix is combined with both kernel/filter to produce a feature map in convolution. Image as an input, for example, might be a multi-mathematical transformation of the red green, and blue value of each pixel [23]. A kernel is chosen, and the input matrix is mixed with it. This combination is now known as a feature map. Convolution decreases the complexity of space and hence improves efficiency. Convolution is the process of combining data in a certain way to decrease space complexity while retaining as much knowledge as feasible.

C. Dermato-Fibroma

Pooling is described as selecting data from the frame in a certain method to maintain information while reducing dimensionality [24]. The greatest value from all distinct combinations in the frame is chosen in max-pooling, integrating only the most important property of that pixel. Pooling reduces the dimensionality of a given representation. For instance, a 3x3 frame size is used over a 10x10 feature matrix, and the biggest value from the existing 9 values is used to depict that feature window. Average pooling is another approach that uses the aggregate of all values in a specific timeframe to represent a feature rather than simply the largest value.

D. Fine Tuning

Transferring the parameters of a trained network and using them to initialize the weights in a model which is being trained on the very same domain shortens the training period and accelerates the process [25]. It permits you to reprocess "feature extraction" from a prior model without having to start from scratch. In fine-tuning, there are two main approaches. One approach is to replicate the entire network as an initiation network and then apply deep learning to it. Another option is to use some pre-trained weights that have been frozen and used for deep learning.

E. Dropout

The "Deep learning" batch normalization method avoids overfitting. Regularization is the practice of resolving neuronal interdependency. This interdependence leads to data overfitting [26]. In dropout, a proportion of neurons, determined by the dropout rate, are disregarded at random throughout each training session. This eliminates the problem of neuronal co-dependency and reinvents each neuron's power [27].

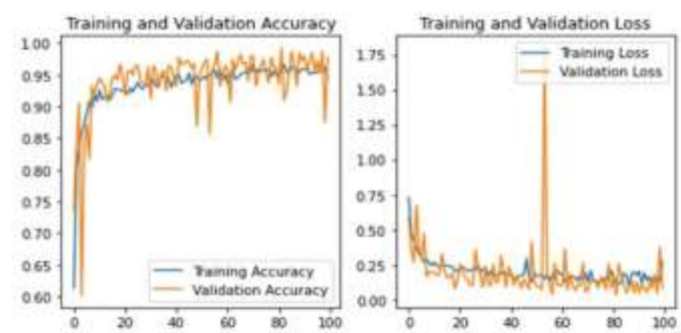

Figure 4. Training and Validation Accuracy Loss

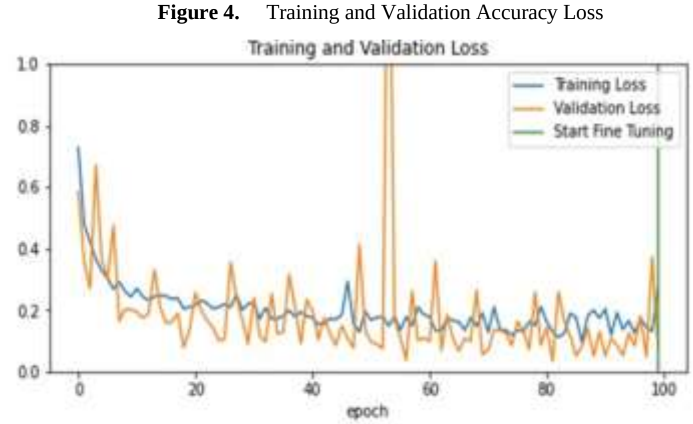

Figure 5. Training and Validation Loss

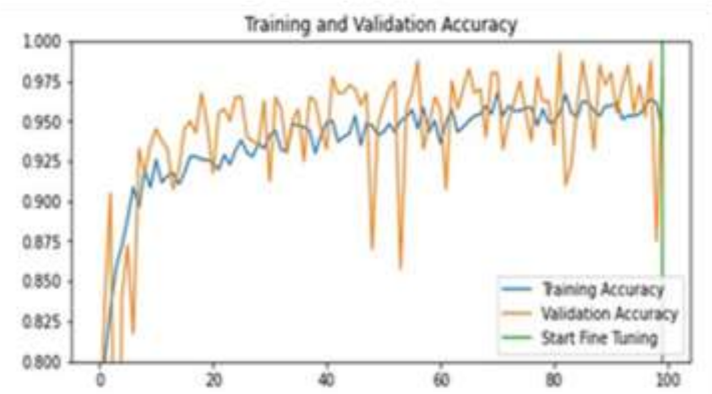

Figure 6. Training and Validation Accuracy (Fine Tuning)

We conducted our experiment on Google COLAB, where we have two distinct folders for testing and training. CNN delivers accuracy of 85 percent after testing and training, but 96 percent after fine-tuning. In our study, we employed a total of 2637 photos from the training dataset and 660 images from the tested dataset to identify melanoma using "Deep learning"[28-29].
The model is also known as sequential KNF in KERAS[30-31]. MATPOLITLIB (for visualization), NUMPY (for multidimensional array objects), KERAS (for artificial neural networks), and tensor flow are the libraries we imported (library for machine learning and artificial intelligence).
Two distinct files of photos were used for testing and training, each of which comprise benign and malignant classifications. Our algorithm's epoch is 40, and we have 40 cycles in our algorithm. We know the input but not the outcome in deep learning, for example, we know what sort of photographs are being categorized. With the distinctions in photos of benign and malignant tumors, deep learning can do structured classification [22]. After scanning the dataset, Deep Learning will categorize the skin as benign (noncancerous) or malignant (cancerous). Deep Learning can address complicated function approximation issues [23]. Classification accuracy may be improved with fine-tuning.

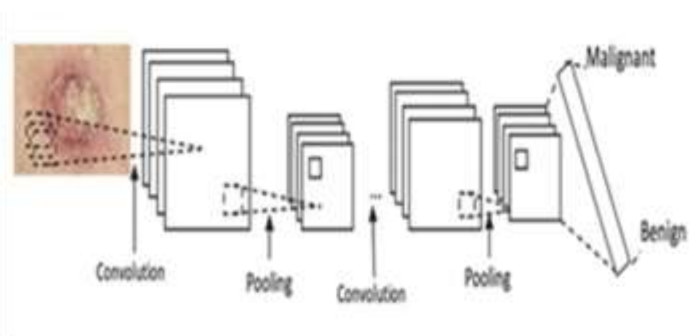

Figure 7. CNN Diagram

V. CONCLUSION

An autonomous classification model based on fine-tuning is furnished, in this paper which classifies the conditions of the benign and normal tumour. This research explored the use of a CNN (Convolutional Neural Network) to identify skin cancer without the use of a clinical test. In the proposed study CNN can detect every benign or cancerous spot on a user's skin with 96 % of accuracy by using the ISIC dataset. The system reveals that the suggested model is prospective enough that can be used as an established tool for medical professionals in evaluating the diagnosis of benign tumors based on performance findings. In future research, a model can be developed to detect and classify multiple tumor features and information as well as other skin illnesses.

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