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Computational Intelligence for Detection of Skin Cancer using Deep Learning Classifiers

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ABSTRACT

Artificial intelligence (AI) has been recognized as an important research field in computer science. Although AI has been around for a while and has been used in many disciplines of medicine, its usage in dermatology is very recent and constrained. Dermatology is a field of bioscience concerned with the diagnosis and treatment of skin diseases. The wide range of dermatologic diseases changes regionally and seasonally according to temperature, humidity, and other environmental factors. Dermatological illnesses have been shown to have major impacts on the behavior of millions of individuals since nearly all forms of skin problems affect everyone every year. Because human analysis of such diseases requires time and effort, and existing techniques are only utilized to analyze certain types of skin diseases, there is a need for higher-level computer-aided skills in the analysis and diagnosis of multi-type skin disorders.

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1. INTRODUCTION

One of the most prevalent illnesses in humans is skin cancer. Dermatological disorders, such as skin malignancies, can be classified into a variety of categories based on their clinical manifestations. Treatment choices and diagnosis differ significantly based on the illness kind and stage. Visual diagnosis in phase 1 clinical skin cancer testing is a traditional clinical approach for classifying the type of skin illness [1]. In the last decade, skin cancer has become one of the most common cancers [2, 3]. Given that the skin is the body's major organ; unsurprisingly, skin cancer is the most frequent cancer in humans [4]. There are several different sorts of skin illnesses, each with its own sets of arguments, like psychological attacks involving hormones and bodily glands, such as acne, or exterior ones involving air pollution or sun sensitivity, like rashes. Scabies and lice are contagious, although medication allergies and rosacea are not. Skin diseases can be chronic, like psoriasis and atopic eczema, or uncommon, like sweet syndrome and ofuji disease [5].

Skin cancer is divided into two types: melanoma and non-melanoma skin cancer. Melanoma is a dangerous, uncommon, and fatal form of skin cancer. Melanoma skin cancer accounts for just 1% of all instances, as per the American Cancer Society, but it is associated with a higher death rate [6]. Melanoma is a kind of cancer that arises in cells known as melanocytes. It begins when normal melanocytes develop out of control, resulting in a malignant tumor. It can impact any part of the human body. It generally occurs in sun-exposed regions, including the hands, face, neck, lips, and so on [2].

Melanoma tumors may only be treated if detected earlier; else, they occur in many areas of the body and the person dies in agonizing [7]. Melanoma skin cancer comes in several forms, including "nodular melanoma, superficial spreading melanoma, acral lentiginous, and lentigo maligna" [2]. "Nonmelanoma cancers, like Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and Sebaceous Gland Carcinoma (SGC), comprise the majority of cancer deaths". BCC, SGC, and SCC are produced in the epidermis' middle and higher layers, accordingly. These cancer cells have a low proclivity for propagating to other sites of the skin. Non-melanoma tumors are easier to treat than melanoma malignancies.

According to research, one-fifth of the population will be impacted by skin cancer at some point in their lives, making detection more difficult [8]. As a result, computer-based illness diagnosis emerges since it can provide a consequence in a short period with more accuracy than human analysis utilizing laboratory procedures. Artificial Intelligence with Deep Learning is the most widely used application for illness prediction. AI may be used to build algorithms to understand the disease's behavior and patterns, and machines then utilize these learning methods to analyze images and forecast. Artificial Intelligence (AI) activates human intelligence in machines, causing them to behave such humans and inherit the learning and problem-solving qualities which human brains possess, allowing them to take the finest decisions possible to attain their objective in the shortest amount of time. It causes systems to imitate it and do activities ranging from the easiest to the most complex, utilizing aims like learning, reasoning, and perception [9].

Since artificial intelligence is now an inherited feature in computers, several of the earlier benchmarks that included it are no longer regarded to represent it. A multidisciplinary method based on mathematics, computer science, linguistics, psychology, and other disciplines is used to wire machines. As a result, computers can comprehend even complicated issues without being outlined in the following via supervised learning that people consider difficult to comprehend. They're utilized in the healthcare business to process large, complicated information and transform them into medical findings [9]. Deep learning, unlike machine learning, employs large datasets and fewer classifiers, leading to longer training times.

This paper adequately analyzes and examines deep learning-based skin cancer detection algorithms. This study presents a detailed, systematic literature study of traditional deep learning techniques for skin cancer diagnosis, including Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Residual Neural Networks (RNN), and Generative Adversarial Neural Networks (GAN). We propose using DL, which has been improved with background information, to extract relevant characteristics for better classification of skin disorders.

The rest of the paper is organized as follows: Section 2 reviews previous work as well as related datasets and issues; Section 3 describes the proposed solution and also corresponding methods and tools; Section 4 presents the results of experiments and discusses their significance; and finally, Section 5 concludes with some thoughts and recommendations for future research.

2. RELATED WORKS

The study of image analysis-based skin cancer detection has progressed substantially over the years. Several various methods have been considered. Skin illnesses are the fourth most prevalent cause of skin disease in the globe. To alleviate this load and to assist patients in doing an early assessment of the skin lesion, a robust and automated method has been created. This method is mostly used in the literature to classify skin cancer. Skin treatments are more successful and less disfiguring when detected early, however, research is difficult owing to the comparable features of skin disorders. We're attempting to identify skin disorders in this research. In this study, a new approach for detecting the most frequent skin lesions is described.

[10] Proposes a method that includes pre-processing, a deep learning method, model training, validation, and classification. Experiments on 10000 images revealed that Convolution Neural Networks with the Keras Application API obtain 93 percent accuracy for seven-class categorization. For the segmentation of skin lesions, Gomez et al. presented an unsupervised method called Independent Histogram Pursuit (IHP) [11]. The system was tested on five distinct dermatological samples, with a competitive accuracy of around 97 percent. In dermoscopic images, Zhou devised multiple mean-shift-based methods for segmenting skin lesions [12]. Garnavi et al. [13] developed an automated skin lesion segmentation method based on optimum color channels and a hybrid thresholding methodology. Pennisi et al. used Delaunay Triangulation to extract binary masks of skin lesion areas in a recent study [14], which did not involve any training.

Ma presented a unique deformable model for skin lesion segmentation that is resilient against noise and provides effective and flexible segmentation performance [15]. It uses a specially designed speed function and stopping parameter. For skin lesion segmentation in dermoscopic images, Yu utilized a deep learning technique, namely a fully convolutional residual network [16].

3. PROPOSED METHODOLOGY

Skin cancer diagnosis depends heavily on deep neural networks. They are made up of several linked nodes. In terms of neural connectivity, their organization is comparable to that of the human brain. To address certain challenges, their nodes collaborate. Neural networks are programmed to perform certain tasks, and then they perform as specialists in the field in which they were programmed. Neural networks were trained to identify images and discriminate between different forms of skin cancer in our analysis. Figure 1 illustrates several kinds of skin diseases from the International Skin Imaging Collaboration (ISIC) dataset [17]. For skin cancer detection systems, we looked into several learning approaches including ANN, CNN, RNN, and GAN. This section focuses on the methodology of each of these deep learning models.

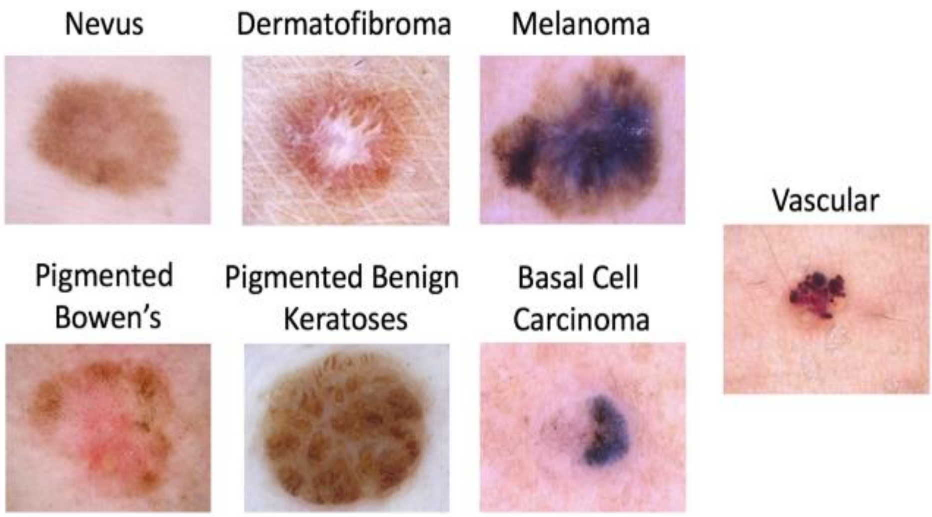

Figure 1. Sample Skin Cancer Images from ISIC Dataset

3.1. Artificial Neural Network (ANN)

Malignant Melanoma is distinguished from other skin disorders through the use of a classifier. Artificial Neural Network (ANN) [18] based classifier is preferred because of its computational efficiency. A feed-forward multilayer network is implemented in this suggested system. For training, the backpropagation algorithm (BPN) is utilized. A minimum of one input layer, one hidden layer, and one output layer is required. The structure of an Artificial Neural Network (ANN) is shown in figure 2. In response to the classification errors, the hidden and output layer nodes alter the value of the weight. The signal flow in BPN will be fed forward, but the error will be backpropagated, and the weights will be adjusted to decrease the error. The weights are adjusted by the error curve's gradient, which leads in the direction of the local minimum. As a result, it is significantly more trustworthy in terms of task classification and prediction.

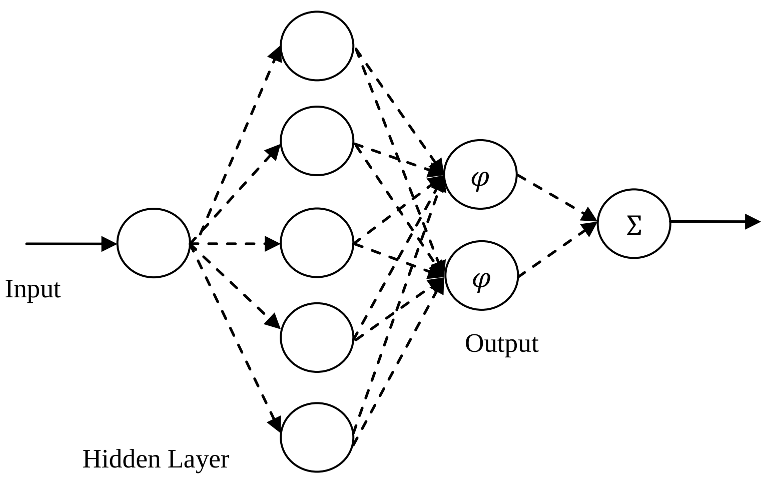

Figure 2. Structure of an Artificial Neural Network (ANN)

Weights are generated at random in BPN at the start of training. There will be a preferred result for which training will be conducted. In this case, supervisory learning is employed. The network produces an output during the forward pass of the signal, based on the initial weights and activation function employed. The result is compared to the desired result. An error occurs if the two are not the same. The anomaly is back-propagated during the reverse pass, and the weights of the hidden and output layers are modified. The process is then repeated until there are no more faults. The network is pre-trained using well-known parameters. After training, the network will be able to make decisions.

3.2. Convolutional Neural Network (CNN)

Yann Le Cun, et al. [19] created the Convolutional Neural Networks (CNN), an enhanced form of neural network. Various mathematical learning approaches, including regularization, back-propagation, and gradient descent, can be used with CNN [20]. The convolutional layer, pooling layer, and fully connected layer are the three main layer principles in CNN. Artificial neural networks are well-known as appropriate solutions to a variety of challenging issues in image processing and machine vision due to their excellent performance. The multilayer perceptron features and other similar networks used gradient descent to minimize the error between the network's realized response and the target result, which is a disadvantage of these networks. However, utilizing gradient descent, the solution might become caught in the local minimum and fail to provide the optimal global solution.

For resolving difficult issues, CNN is extremely effective [49]. The Convolution layer in CNN has a large number of weights that are sub-sampled by the pooling layer to provide output from the convolution layer and lower the data ratio of the layer behind. The pooling layer's outputs are then used to inject data into the fully connected layers. Convolutional neuron layers, which incorporate various data for various purposes including image classification and numerous 2D matrices, are a key component of CNN. Since there is no specific procedure for calculating the number of inputs and output. Based on the extraction of local features, this technique may extract the regional properties of the original images. The basic goal of the learning method is to generate certain kernel matrices that will help the problem generate more descriptive statistical. The back-propagation (BP) method was applied in this circumstance to achieve the network's minimal error value. For the network, sliding window-based convolution is used.

The rectified linear unit (ReLU) is used as the activation function for the neurons in this work by a function f(r) = max(r, 0). Max pooling is also used to reduce the size of the network output so that only the highest values are evaluated in the movable grid's following layers. The BP method is a gradient descent-based technique for decreasing neural network error by minimizing cross-entropy loss as the fitness function. The following is a description of this principle:

$$C = \sum_{b=1}^{Y} \sum_{a=1}^{X} - p_b^{(a)} \log r_b^{(a)} \quad (1)$$

Where Y is the number of samples, p_b is the required output vector, and r_b is the obtained output vector of the a^{th} class, which may be calculated using the method below.

$$r_b^{(a)} = \frac{w^{f_b}}{\sum_{a=1}^{X} w^{f_a}} \quad (2)$$

The weight cost is used to build the function F so that it can contain a φ factor to enhance the weight values.

$$F = \sum_{b=1}^{Y} \sum_{a=1}^{X} - p_b^{(a)} \log r_b^{(a)} + \varphi \sum_U \sum_V G_{u,v}^2 \quad (3)$$

Where U is the layer l connections, V is the total number of layers, and u is the connection weight.

A block diagram of a basic CNN for skin cancer detection is shown in Figure 3.

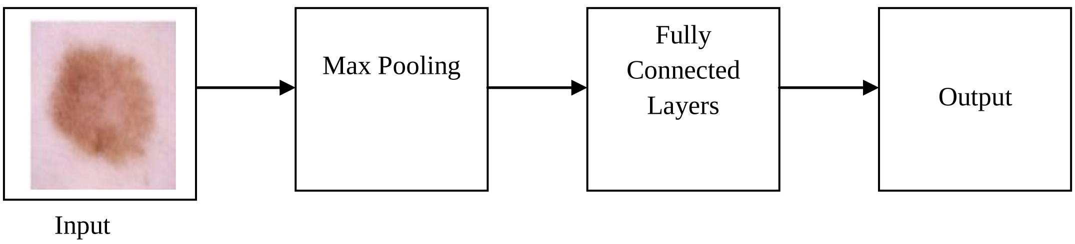

Figure 3. Convolutional Neural Network (CNN)

3.3. Generative Adversarial Network (GAN)

A generative adversarial neural network is a kind of DNN influenced by zero-sum game theory [21]. GANs are founded on the concept that two neural networks, including a generator and a discriminator, interact to evaluate and extract variation in a database. The generator component aims to manipulate the discriminator component by using the data distribution to generate false data samples. The discriminator module, on the other hand, is designed to discriminate between actual and false data samples [22]. Both of these neural networks repeat similar processes throughout the training phase, and their performance increases with each competition [2]. A GAN network's main strength is its capacity to produce false data that are comparable to actual samples utilizing the same data distribution, including photorealistic images. It can also help with a significant issue in deep learning: the insufficiency of training instances. Different forms of GANs, like Vanilla GAN, condition GAN, deep convolutional GAN, super-resolution GAN, and Laplacian Pyramid GAN, have been used by researchers. GANs are now being utilized successfully in skin cancer diagnosis systems. Figure 4 depicts the architecture of a GAN.

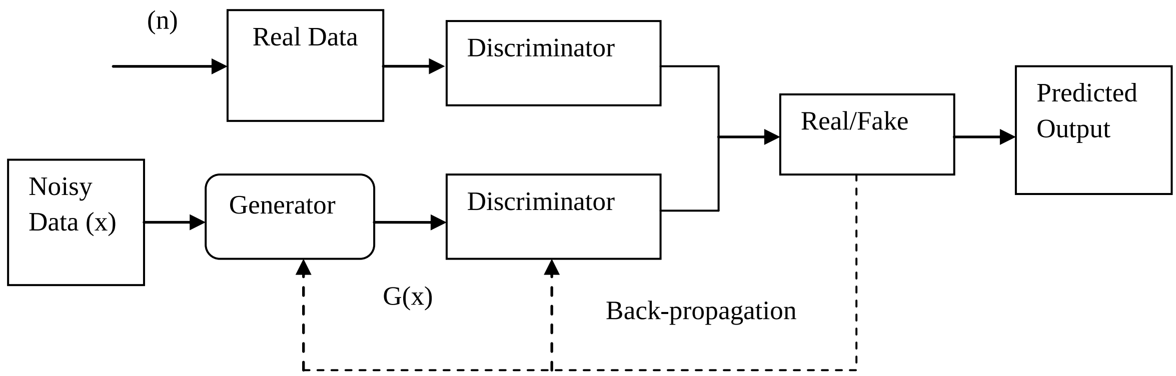

Figure 4. Architecture of Generative Adversarial Network (GAN)

Rashid et al. [23] presented a skin lesion categorization system based on GAN. The suggested method replaced realistic-looking skin lesion pictures produced by GAN in a training batch of photos. The discriminator modules employed CNN as a classifier, whereas the generator modules used a de-convolutional network. CNN learned to identify skin lesions into seven distinct types. The suggested system's results were compared against ResNet-50 and DenseNet. For skin lesion categorization, ResNet-50 had 79.2 percent accuracy, DenseNet had 81.5 percent accuracy. Deep learning algorithms are accurate enough, but they necessitate huge, imbalanced, and pure training datasets. Bisla et al. [24] suggested a deep learning technique for data purification and GAN for data augmentation to address these constraints. For data creation, the suggested system employed decoupled deep convolutional GANs. A pre-trained ResNet-50 approach was chosen to categorize dermoscopic pictures into 3 groups: melanoma, SK, and nevus, using a purified and enhanced dataset.

3.4. Recurrent Neural Network

RNN [25] is a kind of ANN in which the nodes' linkages form a directed graph with a progression of information. It can successfully deal with time-series data, and as a consequence, the result looks to be the best when identifying the current and previous data. A memory cell unit is used in LSTM, which is a kind of RNN. It is made up of three gate units: input, forget, and output. LSTM is also used to resolve gradient mass and explosion. LSTM effectively eliminates superfluous data and seizes the required data in sequence after changing the memory cell unit's state by three gates [26].

GRU is established as a new variant of LSTM that is used to improve the effectiveness of RNN models. GRU integrates the output and forgets gates into a single update gate, EB_i, which uses linear interpolation to help obtain the current result. Assume that $b_i \leftarrow Cr_j$ is the ith input feature and that m_{i-1} is the previously concealed state. Eq. (4) depicts the updated gate, while Eq. (5) represents the reset gate:

$$EB_i = X_{mc}\ (YL^{bEB} b_i +\ X_{mc}\ (YL^{mEB} m_{i-1}) \quad (4)$$

$$PB_i = X_{mc}\ (YL^{bPB} b_i +\ X_{mc}\ (YL^{mpB} m_{i-1}) \quad (5)$$

The activation function, which is a logistic sigmoid function, is represented by X_{mc} from Eqs. (4) and (5). $YL^i = \{YL^{bEB}, YL^{mEB}, YL^{bPB}, YL^{mPB}\}$ is the weight matrix that must be set correctly to minimize the fault mismatch between the anticipated and actual output. Eq. (6) is used to determine the candidate state of the hidden unit, with the element-wise multiplication denoted by $\otimes$:

$$\tilde{m}_i = \tan\ (YL^{bm}\ b_i +\ YL^{mm}\ (m_{i-1} \otimes PB_i)) \quad (6)$$

The linear interpolation between m_{i-1} and candidate state $\tilde{m}_i$ is known as the GRU's ith hidden activation function, m_i, and its equation is Eq. (7):

$$m_i = (1 - EB_i) \otimes \tilde{m}_i + EB_i \otimes m_{i-1}\ m_i = (1 - EB_i) \otimes \tilde{m}_i + EB_i \otimes m_{i-1} \quad (7)$$

The suggested technique maximizes the number of hidden layers in CNN and RNN in this case. The final categorized result is created by executing the AND operation on both the CNN and RNN outputs. The three classifications, including normal, benign, and malignant, are therefore determined using the mammography images as input.

4. RESULTS AND ANALYSIS

The results of experiments utilizing the proposed methodology and the chosen implementation are discussed in this section. In MATLAB 2018a, the suggested melanoma skin cancer detection system was built and evaluated. Our studies employed the ISBI 2016 Challenge dataset for Skin Lesion Analysis for Melanoma Detection. The dataset comprises a typical mix of pictures classified as benign or malignant, divided into 900 training images and 379 test images [27]. The examination of optimal segmentation and classification has been completed in this case. Other algorithms such as CNN, ANN, GAN, and RNN-based models were compared to the optimized segmentation and classification.

To evaluate the system, accuracy, recall, precision, specificity, and the f1 score are used to measure its performance. Recall refers to the number of hazardous cases that could be distinguished from a set of all hazardous instances.

$$\text{Recall} = \frac{TP}{P};$$

The number of benign instances that could be identified out of a whole set of positive cases is referred to as specificity.

$$\text{Specificity} = \frac{TN}{N};$$

The number of threatening cases that the model could effectively foresee out of all the outcases it predicted as harmful is referred to as precision.

$$\text{Precision} = \frac{TP}{TP+FP};$$

To recognize the key principle of how this method works, F1-score is a combination of accuracy and recall.

$$\text{F1-Score} = \frac{2*Prcision*Recall}{Precision*Recall};$$

The images in the ISIC Archive are high-resolution clinical and dermo-scopic images. There is no ontological information about the illnesses provided. Using the deep learning technique, we were able to obtain Top-1 accuracy of 93.06 percent 0.31 percent and Top-2 accuracy of 98.18 percent 0.06 percent with 99.23 percent 0.02 percent AUC. We limited ourselves to Top-2 accuracy because this dataset only includes seven classifications. Table 1 indicates that the deep learning of four classifiers was able to obtain above 80% accuracy for all classes except Vascular Lesions, which could be explained by the minimal number of images in this category. In this dataset, a confusion matrix shows the number of properly classified and misclassified images for each class. Figure 5 shows the comparison of Accuracy of Deep Learning Techniques

Table 1. Performance Analysis of ISIC Dataset using Deep Learning Techniques

Class/Features	Precision	Recall	F1-Score
Nevus	93.1	97.5	93.7
Dermatofibroma (DF)	89.4	78.3	81.5
Melanoma	81.6	61.7	70.8
Pigmented Bowen's (PB)	78.3	70.8	74.2
Pigmented Benign Keratoses (PBK)	82.4	71.6	79.1
Basal Cell Carcinoma (BCC)	88.7	79.5	80.4
Vascular	63.2	68.1	59.3

For a long time, researchers have been interested in automating the detection of skin disorders. Furthermore, even when a large number of classes are known, most of these studies limit themselves to binary or ternary classification. The necessity of melanoma early diagnosis is clear, considering the increasing risk it presents to the patient's survival with each passing day. Thousands of other skin disorders may not be as deadly as melanoma but can have a significant influence on a patient's quality of life. As seen by our results, DL is highly capable of handling hundreds of groups at once. So consider that now is the moment to fully use DL's potential and begin undertaking real-world research that could lead to an industry-standard solution for automated skin disease diagnostics on a wider scale. These technologies have the potential to have a far-reaching societal impact by not only assisting dermatologists in their diagnosis in a clinical setting but also by offering a cost-effective and efficient first screening for disadvantaged individuals in both developed and developing nations. Another factor to consider while using DL in dermatology is that various researchers utilize either private or public datasets, each with their own train/test splits and amount of classes. As a result, as Brinker et al. [45] point out, there is little common basis, and in some cases, no foundation at all, to compare alternative categorization systems. This non-comparability problem may be overcome by compiling and maintaining a standardized, publicly available big dataset with clearly defined train/test splits and standard performance measures for benchmarking. Figure 6 shows the overall performance rate of ISIC datasets with Deep Learning techniques.

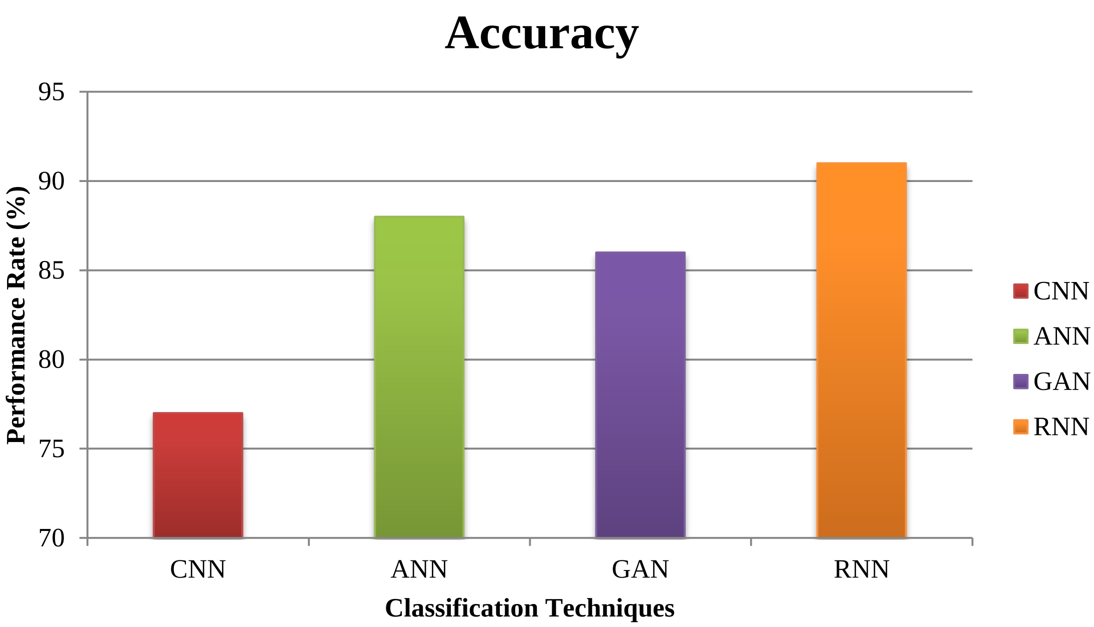

Figure 5. Comparison of Accuracy Rate of Deep Learning Techniques

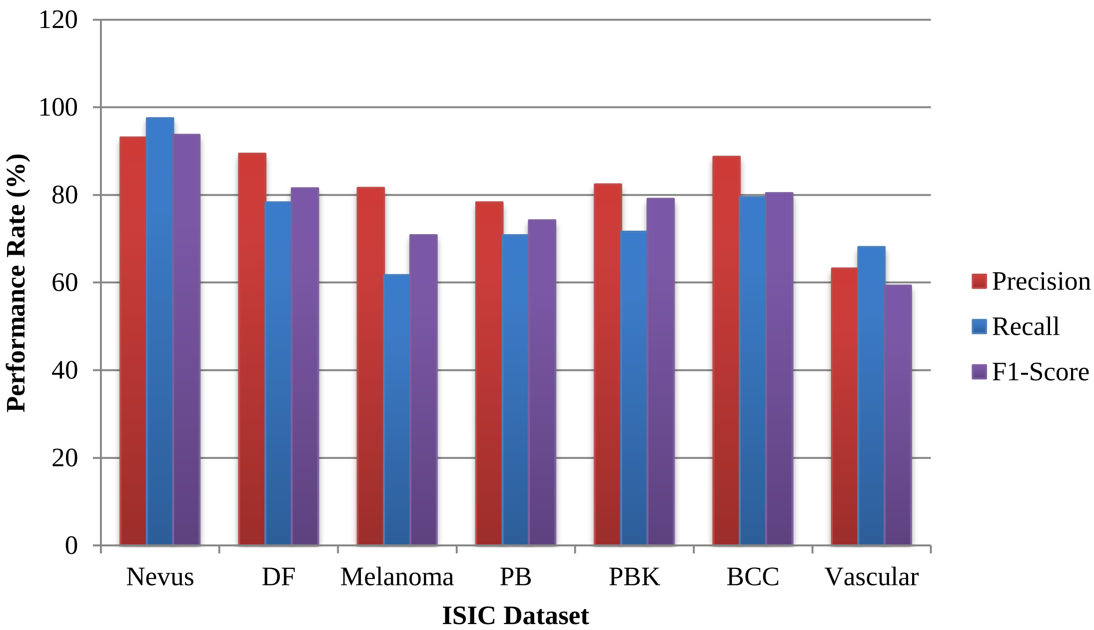

Figure 6. Overall Performance Analysis of ISIC with Deep Learning Techniques

While some public datasets, such as the ISIC Challenges datasets, do give this before-hand train/test split, their size is often modest, and the objective is usually limited to binary or ternary classification. Any study based on these tiny datasets cannot be successfully extended, and while the outcomes are peer-reviewed, they cannot be utilized as a stepping stone to real-world AI diagnosis applications. Large public datasets, on the other hand, frequently contain a lot of noise, photos with embarrassingly poor resolution, or are vectorized. In such low-quality or watermarked images, much valuable information necessary for fine-grained categorization of seemingly identical illnesses is lost. Furthermore, medical image databases seldom include non-visual information such as medical history. This additional information, on the other hand, might be critical for a confident and correct diagnosis. If multi-model datasets are curated and made publically available, AI will be able to use this additional analysis to enhance its classification performance.

5. CONCLUSION

In the detection of skin cancer, AI-based research is showing promising results. Despite claims that deep learning algorithms can outperform physicians in the detection of skin cancer; these algorithms have many more difficulties in becoming a full diagnostic system. Algorithms are never evaluated in real-life diagnoses of skin cancer patients since such trials are conducted in controlled environments. A patient's ethnicity, response to prior therapies, and other information from the diagnosis must all be considered throughout the real-world diagnostic process. Recent deep learning algorithms, on the other hand, mostly rely on imaging data from patients. Furthermore, when such algorithms are used for skin lesions or diseases that are not included in the training dataset, they typically result in a misdiagnosis. This research extended even further into the possibilities for developing techniques to aid doctors in the detection of skin cancer. To enhance existing DL approaches and increase the diagnostic accuracy of techniques used to diagnose skin cancer, computer vision and dermatological organizations must collaborate. DL can bring about a fundamental change in skin cancer diagnosis, as well as a cost-effective, virtually approachable, and efficient health solution.

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