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Health System for Exercise Rehabilitation Detection Retina Images and IoT Blockchain

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Abstract: Smart Healthcare which is based on deep learning is becoming increasingly popular because of its practical applications and has grown popular after its incorporation with IoT. Degenerative eye disease is the main factor of blindness in people of working age. Asian nations with large populations, like India and China, are on the edge of a diabetes epidemic. In terms of medical screening and diagnosis, a large number of diabetes patients posed a huge problem for skilled clinicians. The idea is to employ deep learning algorithms to detect blind spots in the eye and estimate the severity of the stage. We present an optimum approach for detecting blindness in retinal images based on recently released pre-trained EfficientNet models, as well as a comparative assessment of many innovative neural network models, in this study. On a benchmark dataset of retina images obtained by diagnostic imaging at various imaging phases, our EfficientNet-B5-based model assessment performs better than CNN and ResNet50 models.

Keywords: Medical Diagnostic, Retina Images, Internet of Things, Diabetic Retinopathy, CNN

1. INTRODUCTION

The community has recently concentrated on the integration of IoT and AI for smart healthcare. This integration makes it possible to diagnose various health conditions efficiently. Diabetes is a condition that occurs when our systems are unable to produce insulin hormones. According to the World Health Organization[1], diabetes was responsible for the death of 1.6 million in 2016. Diabetes patients have excessive blood glucose levels, which can cause organ failure and dysfunction. According to the International Diabetes Federation (IDF), one in ten people is diabetic. Diabetes consequences include heart attacks, renal failure, severe vision problems, and so on.

One of the most serious effects of this condition is diabetic retinopathy. DR can cause total blindness. It affects millions of people globally[2]. DR affects around 25% of all diabetic patients, making it a complicated illness. Diabetes can produce DR, a degenerative disease that can cause temporary or permanent vision loss. The bulk of those affected by DR are working people, which affects the workforce in a growing economy[2]. According to the IDF, only India has a significant share of diabetes patients globally, and this proportion is rapidly increasing.

Before the development of deep learning, several academics were investigating qualities that might better characterize the core aspects of pictures. HoG , Gist , SURF, SIFT, and other features were proposed at the time. Though they perform well in particular visual tasks, they cannot manage all activities since each feature is created from a distinct component of the image. After the rise of deep learning, the approach has made the development of numerous visual tasks and the segmentation algorithm of medical rehabilitation photos possible[3].

Because a single image feature does not completely use picture information, several researchers have recovered multiple features in different situations to represent visual information more comprehensively. However, because the classifier frequently receives a single eigenvector as input, it must merge several singular eigenvectors to produce a vector[4]. When utilizing the approach of intentionally constructing picture features, however, fewer are obtained and classifier parameters are lowered. Other data, such as smoking history, age, and gender are combined with the expertise of professionals from relevant domains. Solve the problem as quickly as possible, however, the manual description's qualities usually differ for each person, and only operate on certain specific data or fields[5]. Moreover, the generalization ability is limited. Furthermore, this approach has two fundamental flaws. The first difficulty is that as the signal propagates from shallow to deep in the CNN, it becomes gradually attenuated, resulting in fewer and fewer characteristics of the objects in the convolution output. The operation's presence of pooling and other downsampling is the primary cause of this problem. The second difficulty is that the output of the generic CNN is slightly erratic. On one aspect, the single softmax-based classifier is restricted on classification capabilities and ignores the color-pixel distance connection[6].

This study proposes a medical rehabilitation picture segmentation approach that relies on the topological properties of CNN to overcome the aforementioned challenges (HFCNN). To build a hierarchical feature, the technique first samples and then blends the convolution output of multiple layers in a CNN. Second, the picture may be divided into numerous superpixels using the segmentation approach. The training of the classifier is based on the hierarchical properties of the superpixel, and the classified result is sent back to the pixel. Then, a linked conditional random field approach with paired potential energy is developed. The matching energy function smooths the pixel's categorization output, enhancing the geographical homogeneity and continuity of the pixel mark. In comparison to many traditional CNN techniques, our algorithm not only improves network convergence and shortens training time, but also significantly improves the accuracy of the picture segmentation algorithm in medical exercises, demonstrating practical utility[7].

Our paper's technological contributions, in particular, are summarized as given below:

Firstly, the paper examines the recent research status related to the segmentation algorithm of medical exercise images, briefs the common algorithms, and investigates the related deep learning algorithms, which is a CNN.

2. CONTRIBUTION

The following is the key contribution of this work:

- We applied the cutting-edge EfficientNet model in the first instance to detect signs of blindness and identified a significant improvement in blindness identification in retinal images, outperforming CNN and ResNet50 models with over 92 percent validation accuracy.

- We developed a Polar unrolling, a novel augmentation procedure that significantly improves the accuracy of prediction in test time augmentation for the unbalanced dataset of retinal images.

3. RELATED WORK

Researchers have now started to work on healthcare IoT (HealthIoT), linked smart health, and patient monitoring, all of which have great potential for AI technologies. These tools and technology will benefit global health[8], notably in the case of diabetic retinopathy. Researchers have investigated numerous difficulties in eye care. By 2020[9], India should be able to provide adequate care and viable cures for a wide range of eye disorders that might lead to visual loss. Bhalla et al. proposed an effective approach for addressing the problem of DR by holding programs that offer certification for improving their knowledge and abilities for DR identification.

Current cutting-edge DR diagnosing techniques demand ongoing patient observation by a competent physician. These diagnostic approaches take more time and rely on the accessibility of expensive medical equipment. Only a few dozen physicians are in charge of manually detecting

According to the world's largest eye care center, Aravind Eye Hospital in India, over 2 million retinal images are collected every year[10]. They have reintroduced the task's severe difficulty on the basis of time and infrastructure when a significant proportion of cases are typical. The automation of this procedure can help clinicians efficiently diagnose DR patients. Researchers utilized the ML(Machine Learning) approach that predicts the existence of DR. We will go through some of the most notable research on this issue in the following sections[10].

4. METHODOLOGY

ConvNets, depending on resource availability, are scaled for increased accuracy. This scalability can be accomplished in a variety of ways. By increasing the number of layers, we may grow ResNet from ResNet-18 to ResNet-200. To step up a ConvNets model, utilize pictures with high resolution for test sessions. Moreover, the above-mentioned approaches do not effectively assess the breadth, depth, or resolution of the picture. Thus, EfficientNet, a more precise deep ConvNets, is used in this work for identifying DR. EfficientNet scales up on all dimensions using well-defined parameters, resulting in better accuracy[10].

4.1. Medical Exercise Rehabilitation Image Segmentation Algorithm and Deep Learning Algorithm

These rehabilitation images help in focusing and extracting data on specific tissue areas which ultimately helps in producing a much more detailed analysis of the underlying disease.

A. Introduction to Segmentation

Medical rehabilitation image is one of the key research topics in the medical field with the help of IoT. Satisfactory results have been obtained in this field of research and we will have a look into this topic in this article. These rehabilitation images help in focusing and extracting data on specific tissue areas which ultimately helps in producing a much more detailed analysis of the underlying disease. The role of image segmentation is extremely important in such cases. Real life examples such as image- guided surgery, tissue structure and tumor radiotherapy are highly in need of accurate segmentation in order to provide the desired output[11].

As the development progresses in the future, the main segment in which segmentation algorithms of medical rehabilitation image can improve is higher precision as well as faster computational efficiency. A lot of research has been done and good results have been achieved in this field but due to the high requirements and other factors, the present day’s segmentation algorithm is not good enough to meet the needs of medical usage. Hence this topic still remains as one of the most researched topics of medical image analysis. The computer-aided diagnostics has future development prospects in the applications of these topics[12].

A lot more methods are also available for the algorithms of image segmentation and each contain unique features and applications, like the algorithm based on region, algorithm using similarity, algorithm using detection of edges and algorithms using the concept of deep learning, etc.

Figure 1: Watershed Algorithm based on Medical Image Segmentation

Algorithms based on region are classified into two types and they are splitting- merge algorithm and regional growing algorithm. The main objective of the region-growing algorithm is to group together a certain set of pixels that share similar features and characteristics and create a region of them that are combined in order to satisfy the purpose of segmentation as shown in Figure 1. Another way of approach is choosing the seed pixel which means selecting a pixel from the target area. This pixel will be used as the starting point of the regional growth. After this, the pixels that have the same or similar pixels surrounding it will be merged. This process continues as a cycle till the designated task is completed. The other type of algorithm is region split-merge algorithm[13]. The method of this algorithm is that the necessary regions of an image are combined together through splitting. It differs from the first type of algorithm we have discussed as this type follows a procedure of splitting the image into many regions and makes sure that they don't overlap and then merge and split further according to the segmentation requirements.

In the watershed algorithm, the main purpose of it is to extract objects that are similar and consistent from the background

1. Edge detection algorithms use the principle of finding a pixel's gray value present in the image. There will be a noticeable change in gray value and the segmentation of image is done by observing the required uniform area of the edge. This edge is further classified into parallel edge detection and serial edge detection algorithm

2. Deep learning algorithms are one of the recent fields of technology that are showing rapid development in the field of medical image segmentation. Satisfactory results have been obtained in the topics of breast image segmentation as well as in the brain lesions segmentation.

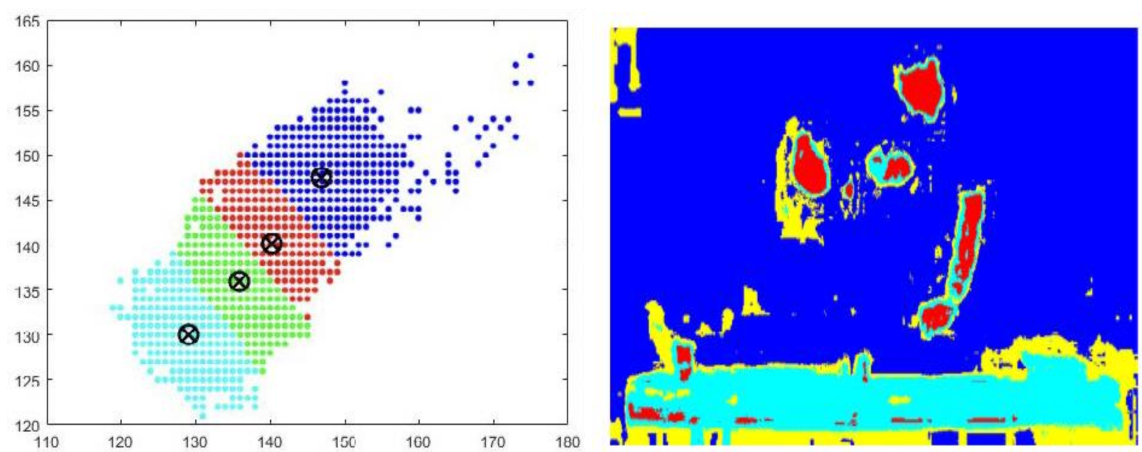

Figure 2: K- Means Algorithm based on medical image Segmentation

B. Introduction to Deep Learning Algorithms

A.I. aka Artificial Intelligence is one of the most rapidly developing engineering branches and is also one among the fastest growing sectors in modern day technology with a huge demand in the market. Due to such rapid development, articles such as various computer technologies are defeating humans in many fields have also been circulated among the society. Advances in fields like storage and development of big data have made computers very powerful that can process and store large amounts of data. Machine learning is a branch that is related to Artificial Intelligence as shown in Figure 2. It can also be mentioned as an algorithm that predicts the analysis of data or instructions given by using the learned set of rules of the machine[13].

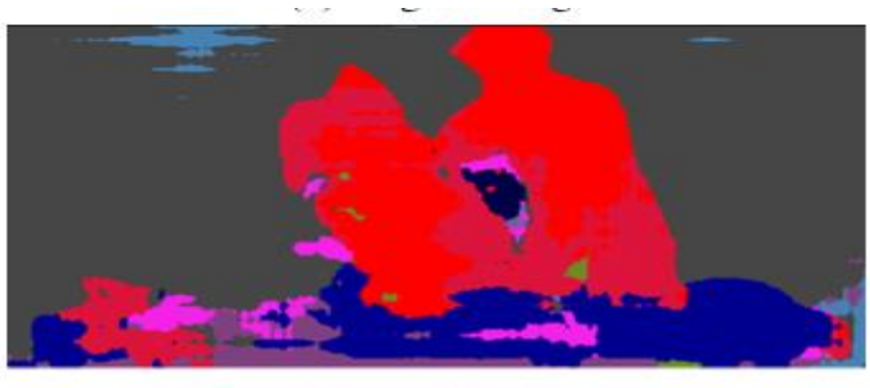

Figure 3: Deep Learning Algorithm based on medical image Segmentation

The similarity between the traditional neural network and deep learning to be noted is that both have a similar hierarchical pattern which includes networks that contain various layers like the input layer, the hidden layer and the output layer[15]. A difference to be noted is, in traditional neural networks, there are two to three layers of networks and they contain certain limitations. Whereas in the other type, i.e., "the deep learning networks", they have more layers and each of these layers are capable of analyzing and executing algorithms as shown in Figure 3. Its structure can be compared to the structure of a human brain.The deep learning architecture comprises neural networks with multiple layers due to which it is also referred to as a deep convolutional neural network. The algorithm can utilize a limitless number of layers to extract features from input data and visualize it. Hubel & Wiesel investigated the neural response generated by a cat's cerebral cortex to stimuli in the 1960s and discovered a unique brain structure parsing and transmitting data and, proposing a volume. The neural network concept was transformed into the deep learning algorithm that we commonly use today[16], as a result of researchers' tireless labor and in-depth research. Using layer-to-layer convolution procedures. The convolution kernel parameters are automatically modified using the training process for neural networks, resulting in an unsupervised generation of manifold parameters of the convolution kernel considered the best fitting for extraction of suitable features from images.

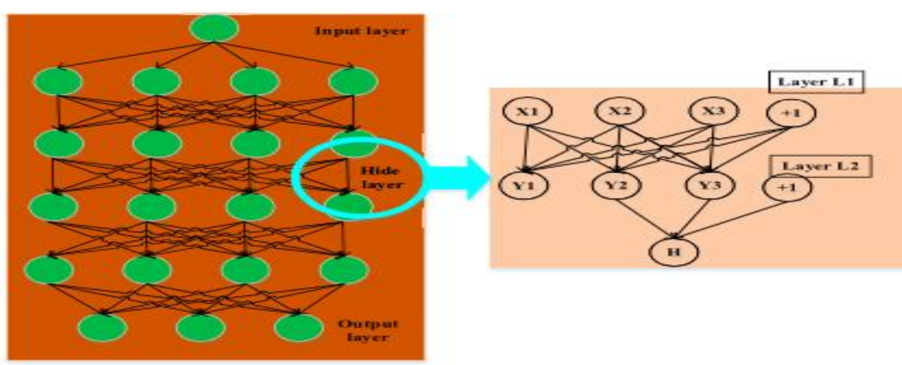

Figure 4: Deep Learning Algorithm based on Multi - layer learning model

4.2. Selection of Network Layers

Because the expanse of hidden layer nodes in the Convolutional Neural Networks (CNN) and Stacked Auto-Encoder (SAE) algorithms used are randomized, along with random weights and offsets in the hidden layer as shown in Figure 4, to optimize the training results only the number of hidden layer nodes needs to be adjusted. The greater number of hidden nodes used in the algorithms, the better it fits the training data, in theory[17]. However, having an excessive number of nodes can prolong the training time. The number of hidden layer nodes must be chosen after a thorough evaluation of the complexity of the algorithm and data retention.

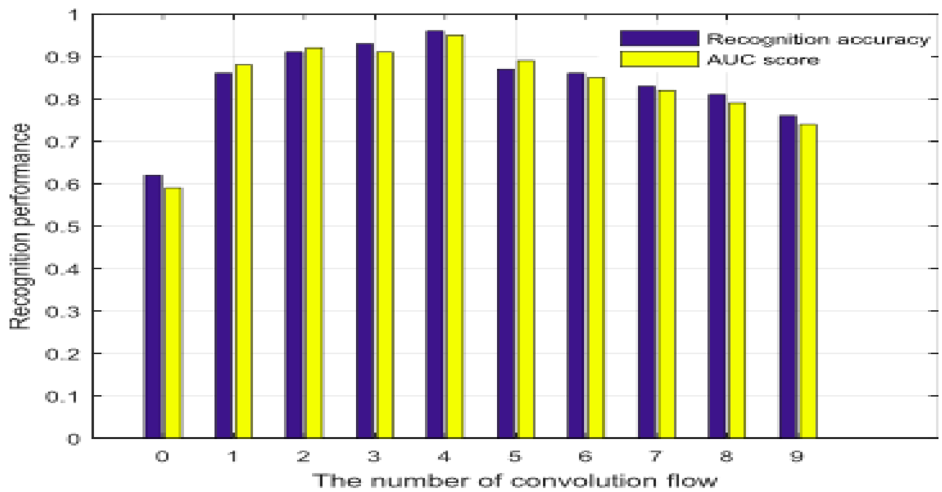

Figure 5: Accuracy rate of recognition and AUC score in relation to the number of convolution flow curves.

The right number of network layers is selected by increasing the number of layers as a convolutional stream. These convolution streams are made up of convolutional and pooling layers[18], both of which are recursively generated from a single convolutional stream. As shown in Figure 5 depicts the outcome of the experiments. As seen in Figure, the recognition accuracy rate and AUC values improve but then drop as the number of convolutional streams increases.

Table 1: Convolutional combination different layer experimental results

Method	MPA	MCA
CONV1+ CONV3+CONV5+CRF	0.82	0.71
CONV1+ CONV4+CONV5+CRF	0.81	0.70
CONV1+ CONV3+ CONV5	0.79	0.69
CONV3+ CONV4+ CONV5	0.78	0.68
CONV1+ CONV5	0.76	0.67
CONV1+ CONV3	0.75	0.65
CONV3+ CONV5	0.74	0.65

It is observed that recognition impact is optimum when five convolution streams are used. Selecting three completely linked layers for classification after deciding on the number of convolution streams. Every 1000 iterations, as shown in Table 1 the network algorithm iterates its training 5000 times and records the resulting trained algorithm[19]. The mode of learning rate attenuation is set to Poly with power = 0.5, and the initial value of starting learning rate is 1.0×10^{-3} as shown in Table 2 and Table 3.

Different convolution Combination

1. Pixel accuracy

$$PA=\frac{pixel\_ok}{pixel\_total} \qquad (1)$$

2. Class precision

$$CP=\frac{\sum_{i\,\epsilon classes}^{n}\ \frac{pixel\_ok}{pixel\_total}}{n} \qquad (2)$$

Table 2: Performance comparison between convolutional layer

Model	Specificity	Sensitivity	Accuracy
HFCNN	0.92	0.95	0.93
Le Net -5	0.75	0.75	0.74
FCN	0.71	0.73	0.72
Alex Net	0.61	0.61	0.60
U-Net	0.82	0.82	0.86

Table 3: Single image comparison for Time Taken

Model	Time
HFCNN	0.03
Le Net -5	0.74
FCN	0.72
Alex Net	0.60
U- Net	0.86

5. CASE STUDY OF SMART IOT-BASED HEALTHCARE SYSTEM

Integration of deep learning technologies enhances the capabilities of the current day IoT-based healthcare systems. Electronic healthcare research and industrial applications have been transformed by recent advances in IoT technology. The widespread usage of IoT powered health devices has drastically improved the overall standard of health monitoring, diagnosis [20], and data collection for doctors, allowing them to make early diagnoses and give timely treatment. However, data security and sharing policy are concerned about the use of patient's private medical data and records. Blockchain offers a way to cope with data privacy and openness. As shown in Figure 6 depicts an IoT & blockchain-based smart healthcare platform. The framework includes a monitoring system for vital signs, an IoT server along with a blockchain network, and a communication interface for compiling data from the medical sensors. All of the data is safely kept and transferred to medical personnel for further medical evaluation.

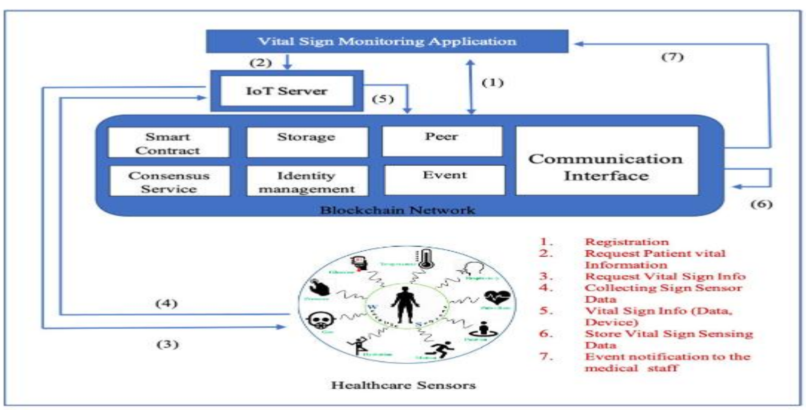

Figure 6: Blockchain smart healthcare framework based on IoT

This data can also be used to construct decision-making algorithms that use deep-learning to offer correct diagnoses in a timely manner. Once developed, the approach can be refined to create IoT-based smart gadgets, to be used effectively by medical personnel [21].

CONCLUSION AND FUTURE WORK

We present a cutting-edge Deep-Learning based smart health system for detecting diabetic retinopathy, a blindness-causing disease, using a retinal image dataset on the Internet of Things. We've demonstrated that combining IoT and AI can result in a far more effective smart health system[22]-[23].

With 92.32 percent validation accuracy, a fine-tuned model based upon Efficient-B5 outperforms other models like CNN and ResNet50 models in predicting diabetic retinopathy (eye blindness) severity on a scale of 1-5 from the retinal scans of the patient. Our base model, Efficient-B5, upon being fine-tuned, is trained after consultation with doctors, a strategy resulting in production of state-of-the-art outcomes in detecting blindness with a validation accuracy of 90.20%. The freezing and unfreezing results in considerably enhanced prediction for fine-tuned EfficientNet-B5 with an even higher validation accuracy of 92.32%. Only for the before time identification of diabetic retinopathy in patients afflicted with diabetes has the proposed method been developed and evaluated. For the analysis of our observed data, we also used oversampling procedures[24]-[25]. The approach must be thoroughly evaluated and tested before making any conclusions about other medical image-based diagnosis procedures. We discovered that in roughly 89% of the photos, there are more 0's and 2's, indicating no symptoms of diabetic and moderate retinopathy, respectively[25].

For such an imbalanced visual data collection, we plan to use alternative CNN architectures, such as UNet paired with ResNet models and, EfficientNet model with UNet, while also pseudo labeling of the imbalanced dataset to possibly enhance the prediction for specific classes.

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