A Deep Learning Architecture to Enhance Cancer Diagnosis Using Convolutional Neural Network and Discrete Cosine Transform

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ABSTRACT

Deep learning architectures are formed by the composition of multiple linear and non-linear transformations of the data, with the goal of yielding more abstract and ultimately more useful representations. The concept of deep learning is inbuilt with many algorithms which help to train the input data set into different layer of perceptron. The convolutional neural networks, which is one of the specialized deep learning algorithms, is used efficiently for analyzing medical images. This paper presents an architecture for efficient and improved clinical diagnosis in scanned image without losing any information produced by the original image using Discrete Cosine Transform (DCT) and classify the features using Neural Network. This transformation has an advantage of compressing the data sets and expresses the data set in a finite sequence of arithmetic cosine functions. A novel characteristic of this approach is that it extends the deep learning architecture to include an interpretable layer that highlights the visual patterns that discriminate between cancerous and normal tissues patterns, working similar to a digital staining which spotlights image regions important for diagnostic decisions. The deep convolutional network, which is one of the deep learning techniques, is used for the purpose of medical image analysis. Segmentation, abnormality detection, disease classification, computer aided diagnosis and retrieval are some of the application areas of convolutional neural networks. In this paper, a comprehensive review of the current state-of-the-art in medical image analysis using deep convolutional networks is also presented. The challenges and potential of these techniques are also highlighted. When compared to the previous cancer detection approaches, the main advantage of the proposed architecture is the possibility of applying data from various types of cancer to automatically form the characteristics which facilitate to enhance the detection and diagnosis of a specific type of cancer. The technique is applied here for the detection and classification of cancer types based on gene expression data.

Keywords: Deep Learning, Convolutional neural network, Medical image analysis, Discrete Cosine Transform, Cancer detection and classification.

1. INTRODUCTION:

By using developed and automatic computer tools with machine learning under IoT helps in medical analysis by enhancing the reported images. One of the deep learning mechanisms is supervised learning which can be used for detection of cancer and analysis of cancer under gene expression data. Early detection of cancer cells may take more advances to cure with successful treatment. Cancer can be detected by measuring the level of tumor in the blood cells. [1] Detection of cancer can be processed under Computed Tomography which provides cross – sectional image, Magnetic Resonance Imaging which uses magnetic field lines especially for cancer detection and sarcoma in neck and head region, Positron Emission Tomography which uses radioactive tracer that is scintigraphy used for analyzing metabolic rate of cancer cells, Endoscopic Tomography used for inspecting the gastrointestinal tract, bronchial tubes, cervix, prostrate, bladder or head and neck region and Isotopic Tomography which is a radioactive tracer. All those detection process are progressed under image sensing methods. [2] This paper proposed a Discrete Cosine Transform method for image enhancing which helps to enhance an image without losing any information produced by original image.

It is very important to find the accurate and efficient diagnosis process. Basically, there are two methods of detecting tumors in blood cells. First method is Artificial Neural Network (ANN) which is an inter-connected group of nodes similar like neurons in the brain. Artificial neuron is represented by circular node. It a feed forward neural network which uses some sort of programming algorithm. Second method is neural network ensemble which is a learning paradigm based on supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. It also uses feed forward neural network. It processed by selecting output data through weights and forms those data as ensemble. Group of neural networks are designed by divide – and – conquer method. For the negative correlation trained data set, this paper proposed an algorithm based on Convolution Neural Network (CNN) to solve automatically. [3]

2. ARTIFICIAL NEURAL NETWORK – ANN:

ANN is the architectural and computing network with its multi-processing elements for receiving trained input data set and for producing output by using some sorted algorithm. [4]

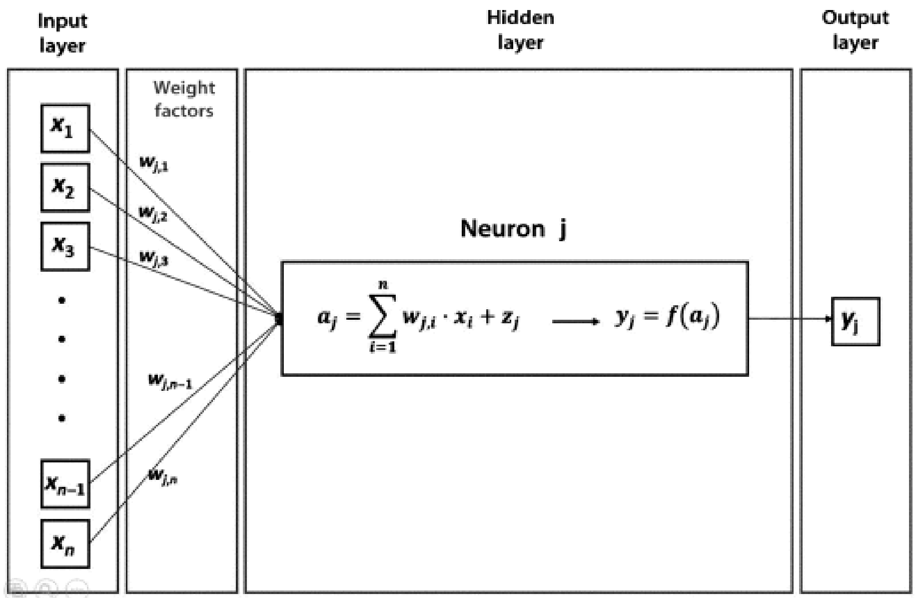

Fig 1 – ANN Architecture with Neurons

2.1 COMPUTATION OF ANN:

ANN scheme in detection of cancer tissues in normal blood tissues is worked with the following processing methods:

Step 1: Initialize array numbers → X_i to input layer of the perceptron nodes.

Step 2: Through the Signal processing between the layers, W_t→ Weights of the data set will amplified with the connections.

Step 3: Through the incoming signals, we can derive the summation of all the adjacent layers.

Step 4: O_j→ Output signal.

$$f(x) = \frac{1}{x + e^{-x}} \qquad (1)$$

Step 5: f(x) output signal which ranges between 0 and 1. Calculation of output from the processed data set is in equation 2

$$Q_j = \frac{1}{1 + e^{-\sum x_i w_i}} \qquad (2)$$

$Q_j \rightarrow$ Output signal. The process will continue until the output layer reached by the signal. For each and every input stimulus, output signal can be response by the interpretation of ANN. [5]

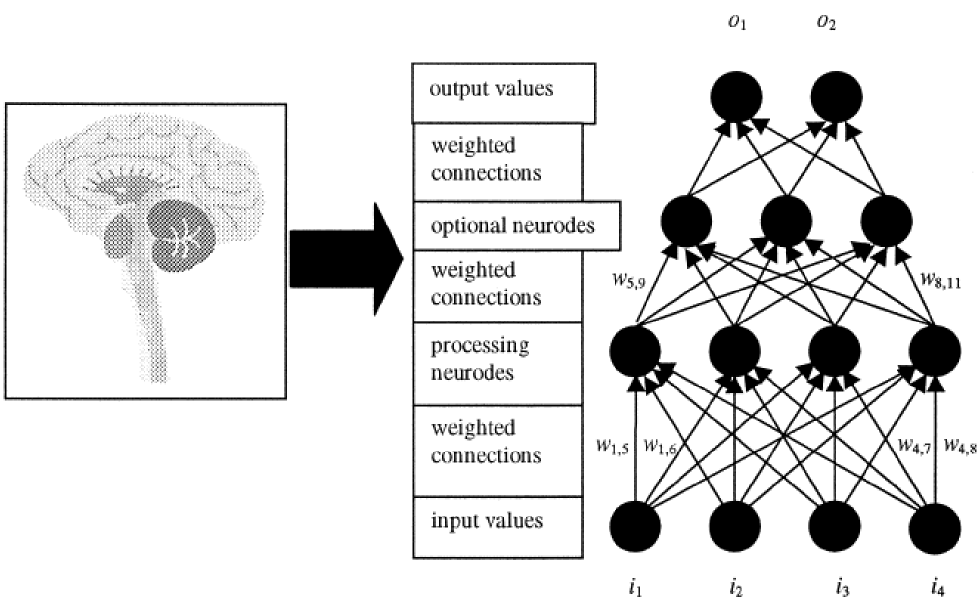

Fig 2 – ANN Structure for Detecting Tumor in Brain Cells

3. CONVOLUTION NEURAL NETWORK – CNN:

CNN is one of the deep learning algorithms which takes input as an image and assign learning weights to the objects in the image which can be differ from one to another. [6]

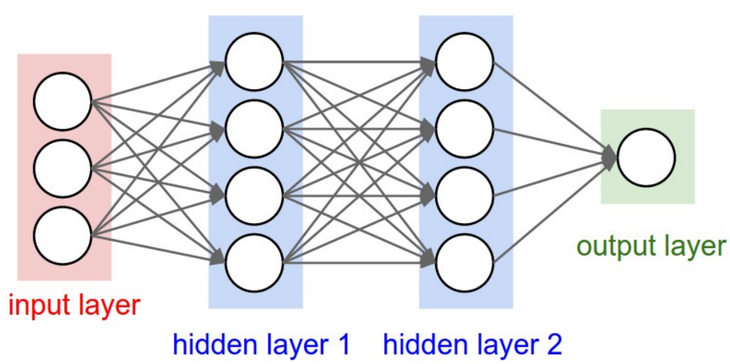

Fig 3 – CNN Architecture For 3 Layers

3.1 LAYERS PRODUCED BY CNN:

Each and every layer of CNN architecture makes the transformations from one volume of activate nodes to another through some integral or differential functions.

Layer 1: INPUT LAYER – Raw pixel values of an image with width 24, height 24 and RGB color combination.

Layer 2 – CONV LAYER – Computation of output by neurons through hidden layers. Each computation process done by dot product between weight measures and its region to the input volume. Results as [24x24x6] if user computes 6 filters.

Layer 3 – RELU LAYER – Applies max(0, x) max(0, x) function to all the elements at zero which produce the size of the volume remain unchanged ([24x24x6])

Layer 4 – POOL LAYER – Along with the spatial domain dimensions, it performs down sampling which results in volume as [12x12x3]

Layer 5 – FULLY – CONNECTED LAYER – Computation of class scores which results in volume as [1x1x5] where 5 represents the number of class score. [7]

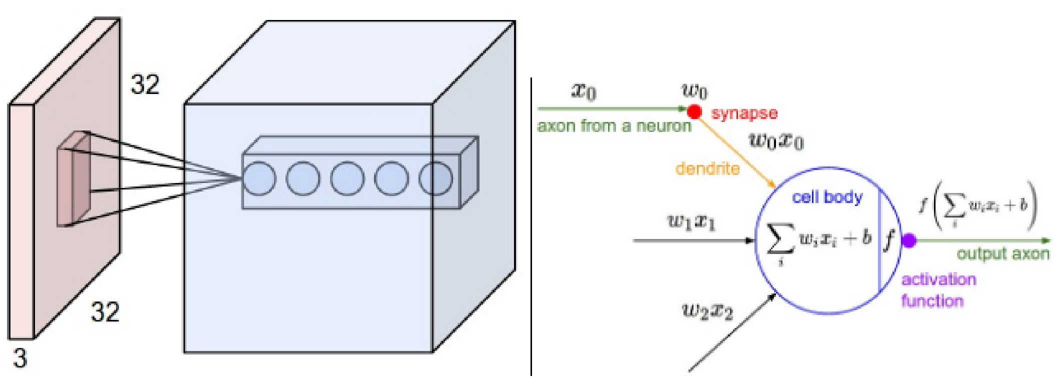

Fig 4 – Computation of Data set to Output

4. DISCRETE COSINE TRANSFORM – DCT:

DCT helps to separate an image into smaller parts for improvement of the visual quality. DCT is similar like Discrete Fourier Transform (DFT) which transforms a signal or an image from spatial domain to frequency domain. DCT is mainly used for compression of an image size. [8]

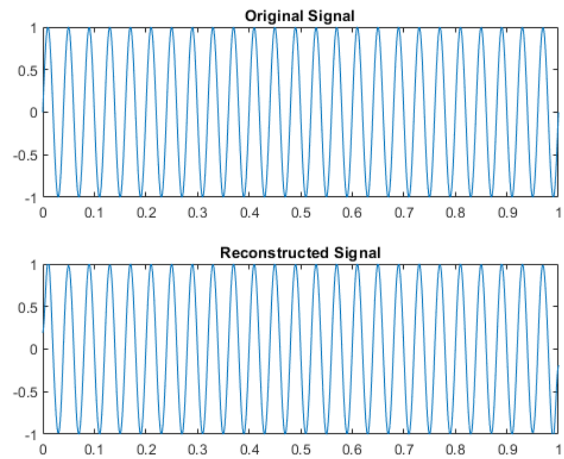

Fig 5 – Conversion of Signals in DCT using MATLAB

4.1 ONE – DIMENSIONAL DCT – ENCODING METHOD 1

The 1 – D forward discrete cosine transform is defined as

$$C(u) = \alpha(u) \sum_{x=0}^{N-1} f(x).cox\left[\frac{(2x-1)\,u\pi}{2N}\right] \qquad for\ u = 0,1,\dots\dots,N-1 \qquad (3)$$

$$where, \alpha(u) = \begin{cases} \sqrt{\dfrac{1}{N}} & for\ u = 0 \\ \sqrt{\dfrac{2}{N}} & for\ u = 1,..,N-1 \end{cases}$$

Similarly, the 1 – D inverse discrete cosine transform is given by

$$f(x) = \sum_{u=0}^{N-1} \alpha(u)C(u) \, . \cos\left[\frac{(2x-1)\, u\pi}{2N}\right] \qquad for \; x = 0,1, \dots \dots, N-1 \tag{4}$$

Equations 3 and 4 are called as 1 – D DCT pair. [9]

4.2 TWO – DIMENSIONAL DCT – ENCODING METHOD 2

The 2 – D forward discrete cosine transform is obtained by

$$C(u,v) = \alpha(u).\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y). \cos\left[\frac{(2x-1)u\pi}{2N}\right] . \cos\left[\frac{(2y-1)v\pi}{2N}\right] (5)$$

$$where, \alpha(u) \; or \; \alpha(v) = \begin{cases} \sqrt{\dfrac{1}{N}} & for \; u = 0 \; or \; v = 0 \\ \sqrt{\dfrac{2}{N}} & for \; u \; or \; v = 1, \dots, N-1 \end{cases}$$

Also, the 2 – D inverse DCT is defined as

$$f(x,y) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} \alpha(u).\alpha(v) C(u,v). \cos\left[\frac{(2x-1)\, u\pi}{2N}\right] . \cos\left[\frac{(2y-1)\, v\pi}{2N}\right] \qquad for \; x, y = 0,1, \dots, N-1 (6)$$

Equations 5 and 6 are called as 2 – D DCT pair. [10]

OPERATIONS OF DCT:

1. The cosine transform ‘C’ is real and orthogonal i.e. $C = C^* \; and \; C^T = C^{-1}$
2. One of the fastest transform is DCT.
3. The DCT of an N element vector can be calculated in $O(N \, log_2 N)$ operations using an N – point FFT as an intermediate step. [11]
4. The computational complexity of direct and FFT based DCT are the same.
5. The DCT has excellent energy compaction for highly correlated images or data.
6. The basis vector of the DCT i.e. the rows of ‘c’ are the Eigen vectors of the symmetric tri – diagonal matrix Q_c.

7. The N x N DCT is very close to the KL transform of a first – order stationary Markov sequence of length N. [12]

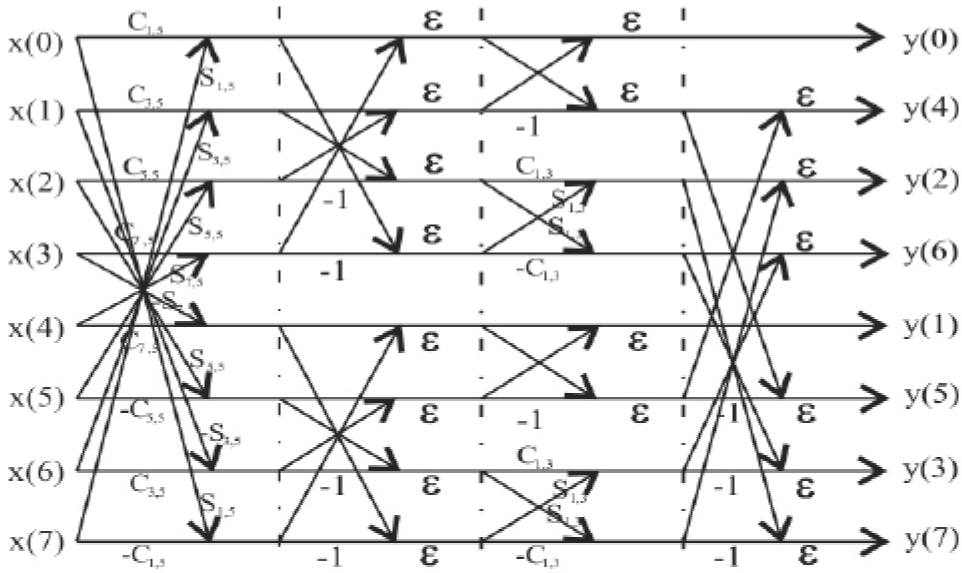

Fig 6 – Fault tolerance of DCT with 8 – Point

5. RESULTS:

CNN using DCT algorithm on cancer tissues:

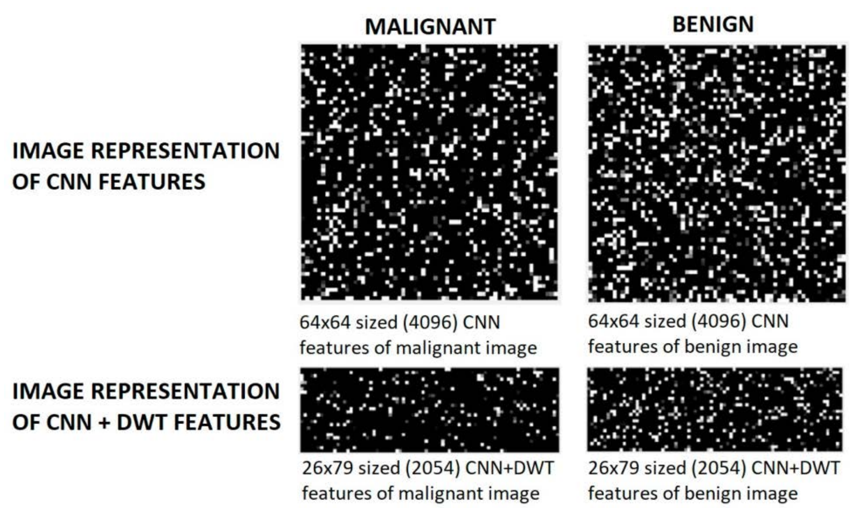

Fig 7 – Result on Brain Cancer Tissues

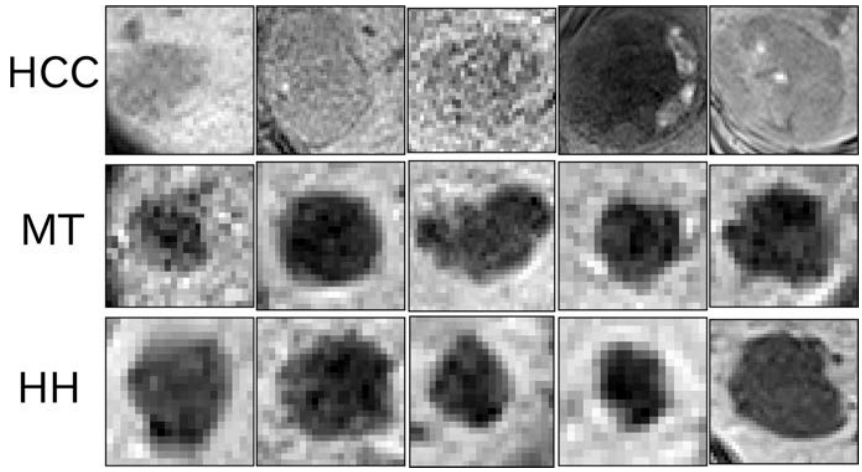

Fig 8 – Hepatic Tumor Classification based on proposed method

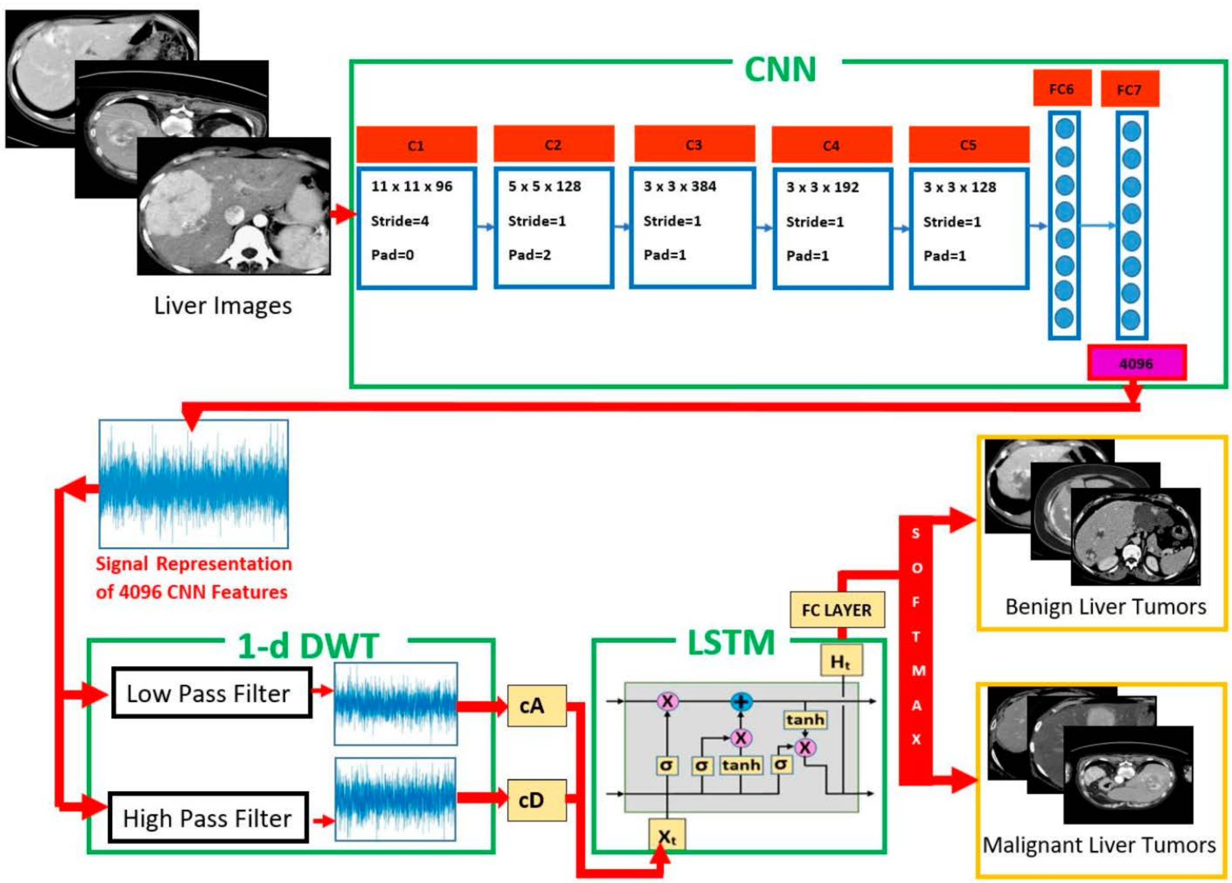

Fig 9 – Classification of Tissues on proposed method

6. DISCUSSION:

Detection of cancer tissues is very important in early stage for diagnosing in the proper method. Quality of image is very important for quality diagnosis. Many approaches in previous paper have derived by detecting the cancer tissues and the diagnosing manner. This paper proposes an efficient algorithm by using Convolutional Neural Network which derives the concept of deep learning for the proceedings of detection. This algorithm is initialized with the collected and trained input data set as an image of size 16 – bits. This algorithm designed in the process of using spatial domain filtering for noise removal. Also the trained data set image is transferred into Discrete Cosine Transform which helps for compression. DCT compress the image without losing the information produced by the original image. This transformation also applied for edges of an image. Fig 7 and 8 explains about the difference of original image and proposed method. Fig 9 shows the flow graph of detecting the cancer tissues and diagnosing methods.

7. CONCLUSION:

Detecting of Cancer cells by using machine learning is an advanced technique. This paper proposed the method of detection of cancer tissues by deep learning which is an emerging technology in machine learning. By using developed and automatic computer tools with machine learning under IoT helps in medical analysis by enhancing the reported images. One of the deep learning mechanisms is supervised learning which can be used for detection of cancer and analysis of cancer under gene expression data. The Convolutional Neural Network which is designed by the mechanism of supervised learning is used in this research article to analyze the growth of cancer tissues. Discrete Cosine Transform is used for enhancing the scanned image for better visual quality.

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