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DISTANCE-BASED COMPARISON OF HOPFIELD NEURAL NETWORK SEGMENTATION USED IN LIVER REGION EXTRACTION FROM CHEST CT IMAGES

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ABSTRACT

Liver cancer is a silent disease because most patients do not have symptoms or indications in the early stages. Early diagnosis is necessary to detect the disease and hence prevent its progression. The aim of our computer-aided detection (CAD) system is to detect liver cancer. In this paper, we study the effect of the distance measure type on the segmentation results of the Hopfield Artificial Neural Network (HNN), which is used to extract the liver region from chest Computed Tomography (CT) images without any pre-processing. We compare three distance measures: the Euclidian distance measure, the Standard Euclidian distance measure, and the Manhattan distance measure. The Euclidian distance measure shows the best segmentation result for the liver region. It also has the best performance in terms of its energy minimization function.

Keywords: *Hopfield Neural Network, Artificial Intelligence, Liver Cancer, CAD, Segmentation, Distance Measure.*

1. INTRODUCTION

Liver cancer is one of the world's most prevalent types of cancer. Worldwide, over 900,000 people were diagnosed with liver cancer, and more than 800,000 liver cancer deaths were recorded in 2020 [1]. Globally, liver cancer is the third most common cause of cancer deaths [2]. In fact, most patients with liver cancer do not suffer from any pain or symptoms in the early stages. Typically, signs appear during the late stages of the disease when the prognosis is generally unfavorable. Therefore, early diagnosis is essential for detecting the disease and, in this way, preventing its progression.

The most common imaging modalities for liver cancer are: Ultrasound scan, Computed Tomography (CT), and Magnetic Resonance Imaging (MRI). Oncologists and radiologists investigate using CT or MRI by looking for any anomalies in shape or texture. Both MRI and CT scans can detect liver cancer at an early stage. However, CT is the most commonly used scanning modality by radiologists and oncologists for liver lesion evaluation and staging[3]. Typically, multidetector CT scanners produce a huge amount of data (e.g., 400 slices per patient), which in turn requires a substantial time input to interpret the data. Thus, developing an automatic system to segment and extract specific images of the liver region is a prerequisite step to handle and interpret these large amounts of data.

Hopfield Artificial Neural Networks (HNNs) have been associated with promising performance in medical image processing[5]. The behavior of the HNN classifier depends mainly on the distance measures.

This work is a part of the HNN-based CAD detection system for liver cancer. In this study, we propose the effect of using three different distance measures on the HNN-based segmentation results of the liver region from chest CT images.

The following sections include related work, an overview of our proposed methodology, findings, and conclusions.

2. RELATED WORK

Image segmentation has been used as the first step in image classification. Many approaches have been used for medical image segmentation, such as histogram analysis, edge detection, regional growth, and pixel classification.

Recently, the use of fully automatic methods has received much attention. There are recognized methods to segment organ regions automatically, such as Artificial Neural Networks (ANNs). ANNs have been proposed as an effective solution for pattern recognition problems. Moreover, adapting deep learning models to undertake supervised segmentation of the liver region and identify tumors is the most prevalent approach in the field of medical image processing. In [6], the authors present the MS-U-Net method, which utilizes the receptive field of Convolutional Neural Network (CNN) with multi-scale features to enable CNN to extract different features at different scales. The proposed method outperforms when it is compared with state-of-the-art methods since the dice score is 97.13% for liver tissue and 84.15% for tumor identification.

In [7] and [8], a special classifier was designed using an unsupervised method which is the Hopfield Artificial Neural Network (HNN), to classify the set of pixels in chest CT images into a set of regions. The HNN is very sensitive to intensity variation, and it is capable of detecting overlapping classes. The results show that HNN successfully located lung contour properly in 95% of the CT scans using a pre-segmentation process based on bit-planes features of the CT scans. Another HNN-based classifier [8] automatically segments the heart region in CT images. The study compared two distance measures in HNN, using Euclidian and Hamming distance measures. The Hamming distance measure showed promising results.

In this work, we compare the effect of different distance measures on the performance of HNN that is used to segment the liver region.

3. METHODOLOGY

In this research, we used HNN at the segmentation stage. At this stage, different types of tissues located inside the CT chest image are classified, such as the liver, lungs, stomach, spleen, kidney, abdominal aorta, gallbladder, adrenal (suprarenal) gland, spinal cords, ribs, and intervertebral disc. Our region of interest (ROI) was in the clusters representing the liver, which can help in accurately determining the liver's borders. In our study, we introduced the Euclidian distance measure as well as two new distance measures to minimize the energy function in HNN: the Standard Euclidian distance measure and the Manhattan distance measure.

3.1. Hopfield Neural Networks

A Hopfield Neural Network (HNN) [9], [10]is a single-layer feedback recurrent neural network. HNNs are categorized as unsupervised learning networks, which means that the network classifies the features without supervision based on the density of each cluster calculated. In the history of neural networks, HNN is an important algorithm since it is considered the modest and most applicable feedback network [10], [11].

HNN classifier architecture consists of a grid of N x M neurons, where N represents the size of the given image and M represents the number of classes given as a priori information. Each column represents a class, and each row represents a pixel. All neurons function as both input and output neurons at the same time. The neurons within each class hold the values of the probabilities that the corresponding pixel belongs to that class. The network is designed to categorize the P features among M classes without supervision using distance measures between the pixel and the class centroid. The segmentation problem can be defined as a partition of N pixels among M classes, such that the assignment of the pixels minimizes the cost-term of the energy function:

$$E = \frac{1}{2}\sum_{k-1}^{N}\sum_{l-1}^{M} D_{kl}^{n} V_{kl} \quad (1)$$

Where D_{kl} is the distance measure between the k^{th} pixel and the centroid of class l, V_{kl} is the output of the k^{th} neuron. The performance of the HNN classifier depends on the distance measure. The definition of D_{kl} for each distance measure will be described in the next section. Minimization is achieved using HNN and by solving the motion equations satisfying:

$$\frac{\partial U_{kl}}{\partial t} = \mu(t)\frac{\partial E}{\partial V_{kl}} \quad (2)$$

where U_{kl} and V_{kl} are the input and output of the k^{th} neuron, $\mu(t)$ a scalar positive function of time is used to increase the convergence speed of the HNN. This function determines the length of the step to be taken in the direction of the vector $d = -\nabla E(V)$. The suitable choice of this step $\mu(t)$ requires some experience. In our work, through experiment, we utilized the function proposed in [8] for segmenting the input image using HNN.

By applying the relation to equation (1), we yielded a set of neural dynamics given by:

$$\mu(t) = t[T_s - t] \quad (3)$$

where t is the step of iteration and T_s is the pre-specified convergence time.

The HNN segmentation algorithm can be summarized in the following stages:

1. Initialize the neurons' inputs to random values.

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2. Apply the input-output relation to obtain the new output value for each neuron, establishing the assignment of pixels to classes.

$$V_{km}(t+1) = 1, \text{if } U_{km} = \mathrm{Max}[U_{kl}(t), \forall\, l]$$
$$V_{km}(t) = 0, \text{otherwise} \qquad (4)$$

3. Calculate the centroid for each class as shown:

$$\overline{X_l} = \frac{[\sum_{k=1}^{n} X_K V_{kl}]}{n_l} \qquad (5)$$

where n_l is the number of pixels in class l.

4. Compute the energy function (E) as defined in (1).

5. Update each neuron's input (U_{kl}) by solving the above deferential equation (3) using Euler's approximation. as next:

$$U_{kl}(t+1) = U_{kl}(t) + \frac{U_{kl}}{dt} \qquad (6)$$

$$1 \le k \le N, \qquad 1 \le l \le M$$

The learning operation occurs when neuron input weights are adjusted to minimize the output energy.

6. While $t < T_s$ go back to step 2. This process iteratively modifies the pixel assignments to reach a close optimal final segmentation map.

3.2. Distance Measures

Our goal in the paper is to study the effect of the type of the distance measure used on the segmentation result of HNN. We undertake the comparison among Euclidian, Standard Euclidean, and Manhattan measure distances used in calculating the distance from the pixels to each cluster centroid, in terms of energy and time.

3.2.1. Euclidian distance (EC)

Also known as the L_2 distance, Euclidian distance is determined as the following equation:

$$D_{kl} = \sqrt{(X_k - \bar{X}_l)^2} \qquad (7)$$

where X_k is the intensity value of the kth pixel, and $\bar{X}_l$ is the centroid of cluster l.

3.2.2. Standard Euclidean distance (STD-EC)

This is Euclidean distance calculated on standardized data. The Euclidian distance is divided by the standard deviation (SD) of the whole image. It can be formulated as shown below:

$$D_{kl} = \sqrt{\frac{(X_k - \bar{X}_l)^2}{SD^2}} \qquad (8)$$

3.2.3. Manhattan distance (MN)

MN is also known as the L_1 distance, or city block distance. It is calculated as the sum of the absolute vector values. The formula is defined as follows:

$$D_{kl} = |X_k - \bar{X}_l| \qquad (9)$$

Both Standard Euclidean distance and Manhattan distance have been used to measure the similarities between two images[12].

4. DATASET

The segmentation process was initially developed and tested on a liver tumor segmentation benchmark (LiTS)[13]. LiTS is a public dataset that includes 201 CT volumes with varying types of tumor contrast levels, abnormalities in tissue size and different amounts of lesions with ground-truth segmentation. The data and segmentations are provided by various clinical sites around the world. Fig. 1 displays an example of one CT scan from LiTS.

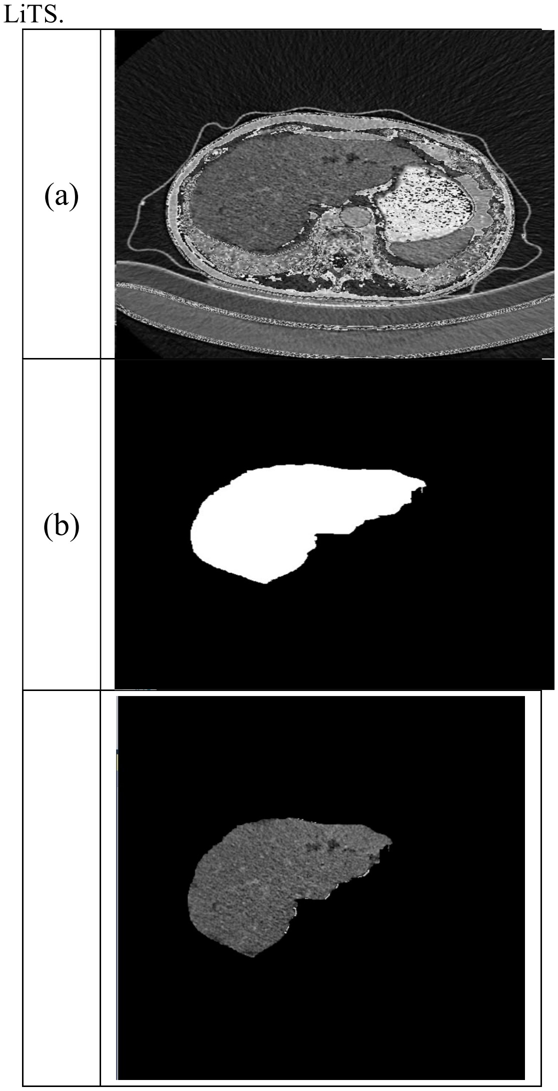

Figure 1: (a)A Chest CT Slice, (b) Radiologists' Mask of ROI, and (c) Extraction of the ROI (Liver Region) Manually.

5. HNN SEGMENTATION RESULTS

(a) Segmentation Results (b) 8-Clusters bar charts

CE

STD -EC

MN

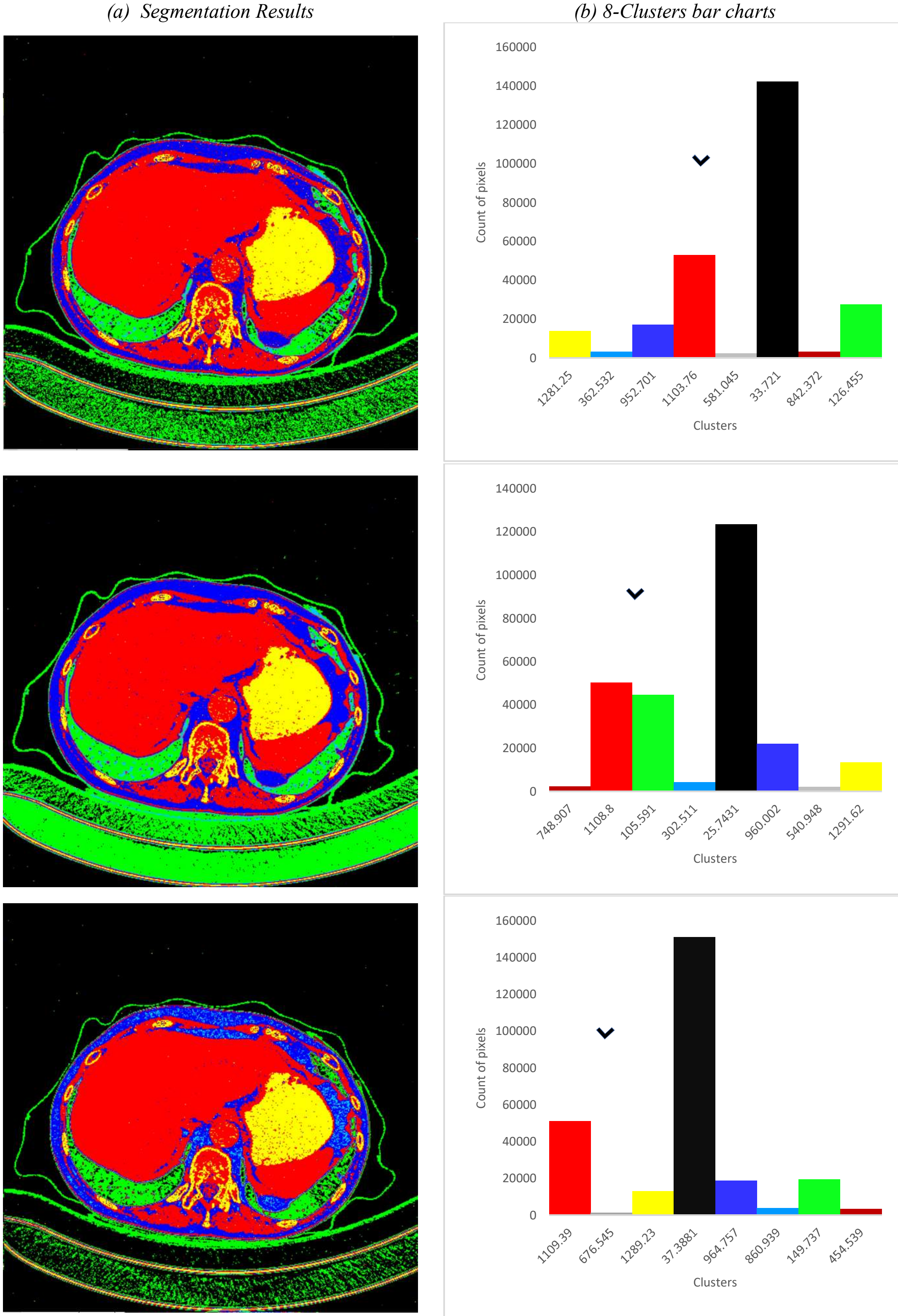

Figure 2: The Images in (a) Represent the Segmentation Results After Applying the HNN Classifier Using 8 Clusters for Each Distance Measure, and the Bar Charts in (b) Represent the Count of Pixels for Each Cluster.

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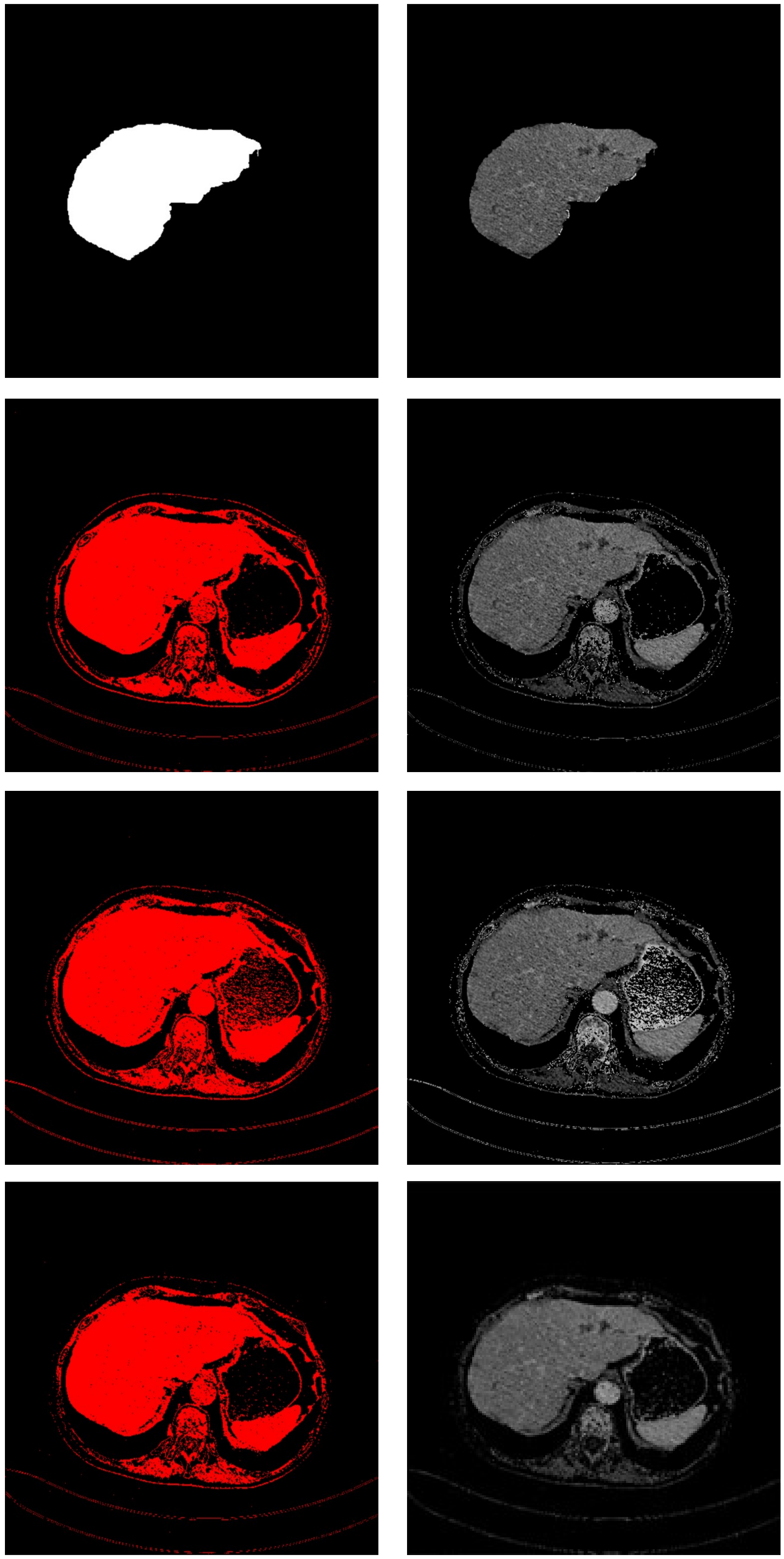

Figure 3: The Binary Masks(a) And the Extracted Areas (b) for the Distance Measures.

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Firstly, we passed the raw CT images without any pre-processing to the HNN classifier. The number of iterations was set to 120, and we altered the cluster number from 5 to 10 clusters as this represented the predicted number of abdominal organs. We utilized the energy minimization function with three distance measures: Euclidian, Standard Euclidian, and Manhattan distance measure.

After applying the unsupervised HNN classifier with 8 clusters using the three distances, some segmentation results are presented in Fig. 2. The clusters are ordered so that the cluster with the highest intensity value is displayed in black, the next cluster with the second intensity value is displayed in red, and so on. The red cluster not only represents the liver area, but also represents other organs with similar intensity, such as the spleen and the aorta, which mainly consist of blood cells like liver cells. It is noticeable that the Euclidian distance measure has the smoothest area for the liver region since it has less noise than the other two distances; then, the Manhattan distance measure comes second. In contrast, Standard Euclidian distance includes the highest noise that includes irrelevant regions, such as the stomach, such noise is an effect of using the standardized formula since it disregards extraneous data.

Table 1: The Summary of Mean Values for the Red Cluster of Each Distance Measure and the Difference to the Real Mean Value of the Liver.

Distance measure	*Mean value*	*Difference*
EC	1103.76	-9.72
STD-EC	1108.80	-4.68
MN	1109.39	-4.09

Table 1 illustrates that the difference between the mean value of the Manhattan's red cluster after HNN-based segmentation (1109.39) and the real mean value for the liver (1113.48) equals 4.09. So, the Manhattan distance achieves the closest mean value to the real mean value for the liver region in the raw image. So, too, the Standard Euclidian achieves a comparable value, which is 4.68, whereas the Euclidian distance measure shows the most remarkable difference (9.72).

We notice that the ROI, which is the liver, is displayed completely with other regions with similar intensity values, as it is shown in Fig. 3. We can also notice that the three distances show extra areas around the liver, which should be excluded and require further segmentation for deep discrimination of different tissue types.

The curves of the unsupervised learning process for all distance measures rapidly converge, as shown in Fig. 4. The curves of both the Euclidian and the Manhattan distance measures have similar performance in terms of their energy minimization function. However, the Manhattan distance measure demonstrates unstable behavior during the learning process. The least energy cost was achieved by the Standard Euclidian distance measure since its formula minimizes energy by dividing the Euclidian distance by the standard deviation. However, it requires a longer time to converge compared to the other two measures.

Table 2: The Summary of Convergence Points After 120 Iterations

Distance measure	*Convergence point*
EC	3401590
STD-EC	6221
MN	4771100

The comparison of the convergence points in Table 2 shows that the Standard Euclidian distance measure achieves the minimum convergence value since its formula potentially minimizes the error rate, as previously mentioned. While the Euclidian distance measure comes second, its convergence point is close to the Manhattan distance measure.

6. CONCLUSION AND FUTURE WORK

In this paper, we have discussed the effect of using different distance measures to assess the performance of HNN-based segmentation to extract the liver area in CT chest images in unsupervised manner. Overall, the results show the Euclidian distance measure outperforms other distance measures. Notably, the ROI segmentation result of the Euclidian distance measure was smooth and covered the entire ROI. Furthermore, its energy minimization function had the best performance over the three distance measures. However, the results of all distances show irrelevant regions that are non-liver tissues are presented which require refinement. Based on this finding, we can utilize the energy minimization function of HNN with the Euclidian distance to segment and then extract the liver region of chest CT images.

In the future, we will use deep segmentation to exclude non-liver tissues to obtain a more precise diagnosis result. We also consider using a cascade 2 HNNs to extract liver tumors using the same distance measure.

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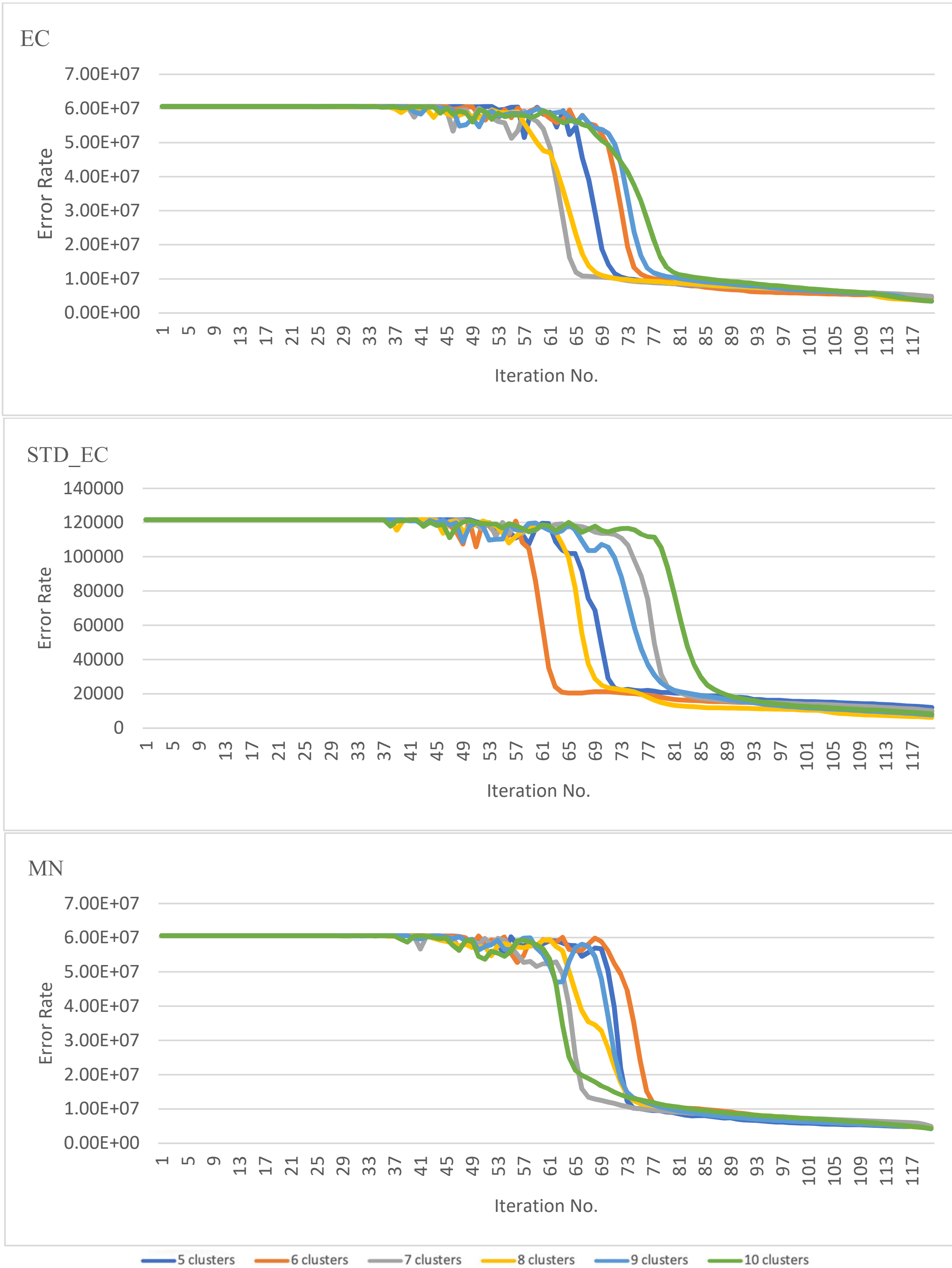

Figure 4: Learning Curves for the Clusters from 5 to 10 Applying HNN With Each Distance Measure.

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