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BONE CANCER IDENTIFICATION USING INTUITIONISTIC FUZZY RANK CORRELATION BASED SEGMENTATION METHOD AND DEEP NEURAL NETWORK

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Abstract:

Bone malignant tumors are one of the important health problems because tumors are formed due to the affectedness of the healthiest bone tissues. This serious bone cancer has been identified with the help of the different risk factors such as chills, swear symptoms, swelling, bones weaken risk, and night swears symptoms. These symptoms are difficult to identify in the beginning stage with effective manner. So, the automatic intuitionistic fuzzy rank correlation based bone cancer detection system has been developed. Initially the bone images are collected, noise present in the images is eliminated with the help of the median filter. After eliminating the noise, affected tumor part is detected by applying the intuitionistic fuzzy rank correlation. From the detected clustered images, various statistical features are extracted which are classified by applying the deep neural networks. Then the efficiency of the system is analyzed with the help of the experimental results and discussion.

Key Words: Bone Malignant, Swear Symptoms, Swelling, Bones Weaken Risk, Intuitionistic Fuzzy Rank Correlation, Median Filter, Deep Neural Networks

1. Introduction:

The national institute in the United States conducting the survey in the year 2016 according to the bone cancer using the 3300 cases. Among the survey most of the people affected both primary and secondary type of bone cancer due to the development of the inflammation, trauma, abnormal growth of the bone tissues [1]. These kinds of bone cancers are identified by using the MRI scan, CT scan and X-ray based screening methodologies. Among the several screening process, X-ray placed an important role due to the accuracy also it detects the cancer from the beginning growth of the tumor cell [2].

Figure 1: Primary and Secondary Bone Cancer Images

Based on the screening methodologies, the bone cancer is effectively detected by applying the different mathematical based image processing technologies such as Gaussian filter, median filter Gaussian filter, edge detection methodologies, mathematics based fuzzy derivation, dual clustering, k-means clustering, scale invariant features, neural networks, linear discriminated analysis and so on [3]. According to the methods, various authors analyze the bone cancer recognition strategies which are explained as follows. Agrawal et al., 2015 [4] recognizing the malignancy utilizing the neural systems in different medicinal research territories, for example, radiology, urology, oncology and cardiology. The neural system devours the element from the past component extraction which is prepared with the assistance of the different actuation work. At that point the prepared elements are perceived utilizing the viable coordinating procedure. At that point the proficiency of the framework is assessed by utilizing the MATLAB trial comes about. The creator created framework guarantees the viable disease recognition venture alongside that it is more practical additionally created framework exceptionally easy to understand when contrasted with the other customary classifiers. Madhuri Avula et al., 2015 [5] breaking down the bone disease from MRI picture utilizing the fuzzy intensity measure. At first different MRI information has been gathered from the diverse information which are prepared by utilizing the picture handling innovations and the got components are prepared by utilizing the fuzzy hypothesis, support vector machine, probabilistic neural systems and learning quantization technique. More over this paper dissect the bone utilizing the k-means grouping calculation which assesses the force of the influenced part by utilizing the specific power esteem. Therefore the creator present bone tumor arrangement handle get up to 95% precision when contrasted with the other acknowledgment techniques with less computational time. Depending on the discussions, the bone cancer has been identified using the fuzzy based [6] mathematical image processing technologies using from the bone cancer images. The detailed derivation of the bone cancer processing methodologies is discussed in the following sections. Then the rest of the section organized as follows, section 2 analyze elaborate mathematical explanation of the intuitionistic fuzzy rank correlation based segmentation process and working definition. Section 3 discussing the proposed bone cancer detection process using the intuitionistic fuzzy rank correlation method. Section 4 examining the efficiency of the proposed system and concludes in section 5.

2. Intuitionistic Fuzzy Rank Correlation Processing Procedure:

Intuitionistic Fuzzy Rank Correlation [7] is one of the most powerful tool which analyze the difficulties between the variables using the particular rank correlation method. During this process, the ordinary or crisp set has been created which consists of the gradual transition of the set variables. Then the independency of the two variables are estimated depending on the correlation between the variables. Consider the data set has $X = \{X_1, X_2, \ldots . X_n\}$, then the correlation between X and Y has been estimated as follows,

$$\rho = 1 - \frac{6[d_i^2]}{n(n^2-1)} \qquad (1)$$

In the above eqn (1), $d_1 = R_1 - R_2$ is the rank of X and Y. The rank is defined based on the qualitative characteristics [8] of the data which helps to correlate the two variables effective manner. Based on the correlations, the intuitionistic fuzzy set is defined as follows for defining the independency between the variables by comparing the membership and non-membership values in the dataset.

Intuitionistic Fuzzy Set:

Definition 1: Let X is the nonempty set, then the fuzzy set A is defined as follows, $A = \{\langle (x) \rangle : x \in X\}$ where $\mu_A(x): X \to [0,1]$ is the membership function of the fuzzy set A.

Definition 2: Let X is the nonempty set, an intuitionistic fuzzy set A in X is defined as, $A = \{\langle x, \mu_A(x), v_A(x) \rangle\}: x \in X$ where $\mu_A(x), v_A(x): X \to [0,1]$ which is belongs to the degree of membership and non-degree of membership element $x \in X \, in \, set \, A$. For every element, $x \in X, 0 \le \mu_A(x) + v_A(x) \le 1$, intuitionistic fuzzy set index is defined as $(x) = 1 - (x) - v_A(x)$ this is also called as the hesitation margin of x. $\pi_A(x)$ is the degree of indeterminacy of $x \in X$ to the IFS A and $\pi_A(x) \in [0,1]$.

Definition 3: Let X be the IFS then, $(x) = 1 - \mu_A(x)$ is defined as degree of indeterminacy of element $x \in A. \partial_A(x) = \mu_A(x) + \pi_A(x)\mu_A(x)$ is degree of favor of $x \in A$ and $\eta_A(x) = v_A(x) + \pi_A(x)v_A(x)$ is called degree of against of $x \in A$.

Definition 4: (Similar IFS) Two IFS A and B are said to be similar if, $\exists \mu_A(x) = \mu_{B(x)} \,^{\circ}r v_A(x) = v_B(x)$

Definition 5: (Comparable IFS) Two IFS A and B are said to be equal or comparable$\mu_A(x) = \mu_B(x)$ and $v_A(x) = v_B(x)$

Definition 6: (Equivalent IFS) Two IFS A and B are said to be equivalent to each other, A is equivalent to B, denoted by $A \to B \, if \, \exists function f: \mu_A(x) \to \mu_B(x)$ and $f: v_A(x) \to v_B(x)$ which are both injection and surjection.

Definition 7: (Inclusive IFS) Let A and B be two IFS, $A \subseteq B \Longrightarrow (x) \le \mu_B(x)$ and $v_A(x) \ge v_B(x) \, for \, x \in X$. Then A is subset B is a superset of A.

Definition 8: (Proper Subset) A is the proper subset of B $A \subseteq B \, if \, A \subseteq B \, and \, A \ne B$. It means, $(x) \le \mu_B(x) and \, v_A(x) but \, \mu_A(x) \ne \mu_B(x) and \, x \ne \mu_B(x) for \, x \in X$

Definition 9: (Dominations) An IFS A is dominated by another IFS B (A$\le B$)if there exist an injection from A to B. A is strictly dominated by B (A<B)

Definition 10: (Relations) Let A, B and C be IFS then, (A$\le A$) i.e A is the reflexive relation, $A \le B \, and \, B \le A$ is the symmetric relation, $A \le B \, and \, B \le C \Longrightarrow A \le C$ is transitive relation. According to the definition, the basic operations of the intuitionistic fuzzy set [9] is defined as follows,

$$[Inclusion] \subseteq B \leftrightarrow \mu_A(x) \le \mu_B(x) \, and \, v_A(x) \ge v_B(x) \forall x \in X \; A^c = \{\langle x, v_A(x), \mu_A(x) \rangle : x \in X\} \qquad (2)$$

Union operation is performed between two variables which are defined as,

$$A \cup B = \{\langle x, \max(\mu_A(x), \mu_B(x), \min(v_A(x), v_B(x)) \rangle : x \in X\} \qquad (3)$$

Intersection operation is done by as follows,

$$A \cap B = \{\langle x, \min \mu_A(x), \mu_B(x), \max(v_A(x), v_B(x)) \rangle ; x \in X\} \qquad (4)$$

Addition operation is done by using as follows,

$$A \oplus B = \{\langle x, \mu_A(x) + \mu_B(x) - \mu_A(x)\mu_B(x), v_A(x)v_B(x) \rangle ; x \in X\} \qquad (5)$$

Multiplication is done by,

$$A \otimes B = \{\langle x, \mu_A(x)\mu_B(x), v_A(x) + v_B(x) - v_A(x)v_B(x) \rangle ; x \in X\} \qquad (6)$$

According to the above discussions, the intuitionistic fuzzy membership and non-membership values are between [0,1] that helps to analyze the particular data or images with effective manner when it applies to the real time applications. Based on the statistical correlation measures, the intuitionistic fuzzy membership value is applied to following bone cancer recognition process.

3. Proposed Bone Cancer Detection Process Using the Intuitionistic Fuzzy Rank Correlation Method:

In this section investigating the mathematical intuitionistic fuzzy rank correlation [10] based bone cancer detection system. The processing steps of the bone cancer detection system are shown in the figure 2.

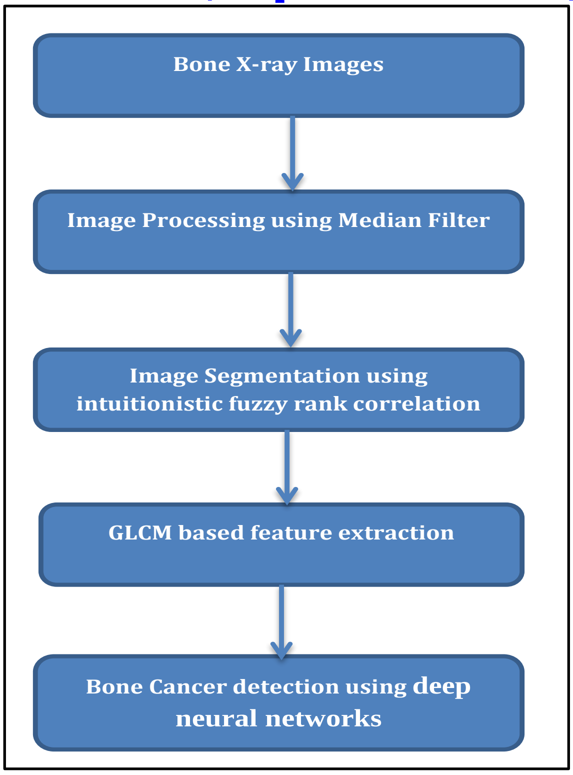

Figure 2: Proposed Bone Cancer Detection Flow

The above figure 2 depicted that the proposed bone cancer detection system working process which includes different steps such as X-ray image preprocessing, segmentation, feature extraction and cancer detection. The detailed procedure of the proposed working process is defined as follows.

Median Filter based Noise Removal Process:

The first step of the bone cancer detection process is noise removal which is done with the help of the median filter [11]. The captured X-ray image consists of various irrelevant information that reduces the entire cancer detection process. So, each pixel present in the images are arranged in the sorting order and compared with the threshold value (maximum or minimum). If the pixel value is not matched with the threshold value, it considered as the noisy pixel that has been replaced with the help of the median filter. The median value is estimated from the sorted pixel value. This process is repeated until to eliminate the entire noisy pixels with effective manner. After removing the inconsistent data, the particular affected region has been segmented with the help of the intuitionistic fuzzy rank correlation based method which is explained as follows.

Intuitionistic Fuzzy Rank Correlation based Image Segmentation:

The next important step is image segmentation [12], in which each pixel is analyzed using the particular fuzzy membership value μ_A and non-membership value γ_A that is lies between [0,1]. But the conventional rank correlation value is belongs to the [-1,1], so, the intuitionistic fuzzy set has been defined as $A = \{\langle x, \mu_A(x), \gamma_A(x)\rangle\}$ and $B = \{\langle x, \mu_B(x), \gamma_B(x)\rangle\}$ which takes the input value as 1,2,3…..n. After that the correlation between each pixel data has been estimated as given in the below.

$$(\overline{\mu_A} - \overline{\mu_B}) = (\overline{\gamma_A} - \bar{\gamma}_B) = \frac{n+1}{2}\sigma_\mu^2 - \frac{1}{2}\sum_{i=1}^{n}[(\mu_A - \mu_B) - (\overline{\mu_A} - \overline{\mu_B})]^2 \quad (7)$$

Based on the above eqn () the noise removed X-ray images pixels are arranged in the intuitionistic fuzzy set, the correlation between the pixels are calculated as follows,

$$\rho = 1 - 6\frac{\left[\sum_{i=1}^{n} d_\mu - \sum_{i=1}^{n} d_y\right]^2}{n(n^2-1)} \quad (8)$$

According to the rank correlations, similar pixels are grouped into together which is helps to recognize the bone cancer with effective manner. From the extracted regions various statistical features are extracted which is listed in the following section.

Statistical Feature Extraction:

The third most crucial step is feature extraction that is performed with the help of the Gray Level Co-occurrence Matrix (GLCM) [13]. The method derived the features from the intuitionistic fuzzy rank correlation based segmented region in terms of both texture, shape and intensity features which is listed out in the table 1. According to the table 1 eqn's different features are extracted with effective manner.

Table 1: GLCM Based Features and Related Formulae

Features	Related Formula
Entropy	$\sum_{i,j=0}^{n-1} -\ln(P_{ij})\, P_{ij}$

Correlation	$\sum_{i,j=0}^{n-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2}$
Energy	$\sum_{i,j=0}^{n-1} (P_{ij})^2$
Contrast	$\sum_{i,j=0}^{n-1} P_{ij} (i-j)^2$
Cluster Shade	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} (i+j-\mu_x-\mu_y)^3 . p(i,j)$
Variance	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} (i-\mu)^2 . p(i,j)$
Mean	$\sum_{i=0}^{2(n-1)} i . p_{x+y}(i)$
Cluster Prominence	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} (i+j-\mu_x-\mu_y)^4 . p(i,j)$
Inertia	$\sum_{i,j=0}^{n-1} (i-j)^2 . p(i,j)$
Skewness	$\sigma^{-3} \sum_{i=0}^{n-1} (i-\mu)^3 . p(i)$
Kurtosis	$\sigma^{-4} \sum_{i=0}^{n-1} ((i-\mu)^4 . p(i)) - 3$

The extracted GLCM features are widely used to analyze the bone cancer by using deep neural networks that is explained as follows.

Deep Neural Network based Bone Cancer Detection System:

The last step of this work is bone cancer detection which is done by using the deep neural networks. Before performing the classification process, the extracted features are trained with the help of the Adaboost technique [14] which successfully supports the weak features. The Adaboost training process is performed as follows

$$f(x) = \sum_{j=1}^{J} \alpha_j h_j(x) \qquad (9)$$

α_j is the non-negative weak features in the pooling layer, h_j is the better features. Based on the above eqn (9) the extracted features are trained which are compared with the testing features for recognizing the bone cancer with effective manner.After that the testing features are fed into the deep neural networks [15] that consist of three layers namely input layer, hidden layer, output layer. Each layer receives the extracted region as input which is processed by using the relative weights and bias values. The trained features are helps to reduces the error rate and the output of the network is calculated as follows,

$$Net\ output = \sum_{i=1}^{N} x_i * w_i + b \qquad (10)$$

During the net output calculation the neural network is trained by using the Levenberg-Marquardt learning algorithm which updates the weights and bias as defined as,

$$X_{k+1} = X_k - [J^T J + \mu I]^{-1} J^T e \qquad (11)$$

This process is repeated continuously, and the output of the bone cancer has been detected according to the training features with effective manner. Thus the proposed deep neural network successfully recognizes bone cancer. Then the efficiency of the system is evaluated with the help of the experimental results and discussions.

4. Experimental Results of Bone Cancer Detection process:

In this section analyze the efficiency of the bone cancer detection process that has been implemented in MATLAB tool. During the implementation, the bone images are collected from the Open-Access Medical Image Repositories [16] that consists of collection different parts of bone images which help to analyze the proposed intuitionistic fuzzy rank correlation based bone cancer detection system efficiency. After collecting the images the noise present in the images are eliminated by replacing the median value and the affected region is successfully extracted with effective manner. From the extracted region, various features are extracted which are trained by using the Adaboost method which is stored as template in database. The new testing features are compared with the trained features using the deep neural networks. Then the efficiency of the system is examined using the following performance metrics[17].

$$True\ Positive\ rate\ (TP) = \frac{Numbers\ of\ features\ detected \times 100}{Number\ of\ features\ in\ the\ dataset} \qquad (12)$$

$$False\ Positive\ rate\ (FP) = \frac{Num ber\ of\ false\ detections\ \times 100}{Number\ of\ features\ detected + Number\ of\ false\ detection} \qquad (13)$$

$$False\ Negative\ Rate\ (FN) = \frac{Number\ of\ features\ missed \times 100}{Number\ of\ features\ in\ the\ dataset} \quad (14)$$

$$Precision = \frac{TP}{TP+FP} \quad (15)$$

$$Recall = \frac{TP}{TP+FN} \quad (16)$$

$$Accuracy = \frac{number\ \ of\ true\ positive + number\ \ of\ true\ negative}{number\ \ of\ true\ positive + false\ positive + false\ negative + true\ negative} \quad (17)$$

According to the above performance metrics, the excellence of the proposed bone cancer detection process is evaluated while segmenting the image and classifying the extracted features from the dataset. The effectiveness of the proposed intuitionistic fuzzy rank correlation based segmentation process is compared with the traditional segmentation methods such as canny edge detection [18], soble edge detection process [19] and fuzzy clustering process [20] which is shown in the figure 3. Thus the proposed intuitionistic fuzzy rank correlation segmentation method achieves the 99.2% accuracy, 97.53% of precision and 98.65% of recall which is shows that the proposed segmentation method effectively identifies the affected region from the dataset that helps to retrieve the features successfully.

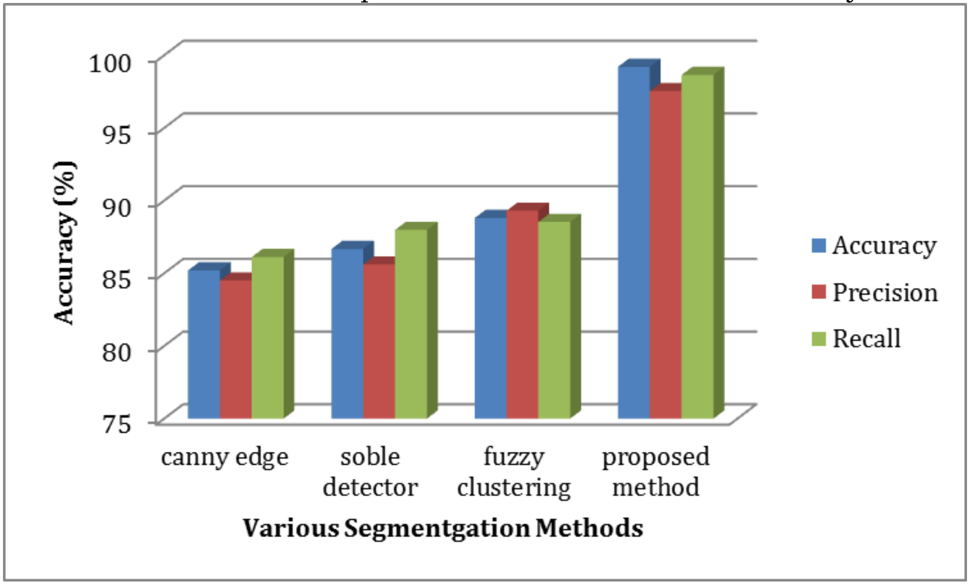

Figure 3: Efficiency of intuitionistic fuzzy rank correlation Segmentation Methods

Based on the above image segmentation methods, the retrieved features are fed into the Adaboost method which successfully trains the features with minimum time. Then the Adaboost based trained features are compared with the traditional training methods such as support vector machine (SVM) [21], Radial basis Function (RBF) [22] which is shown in figure 4.

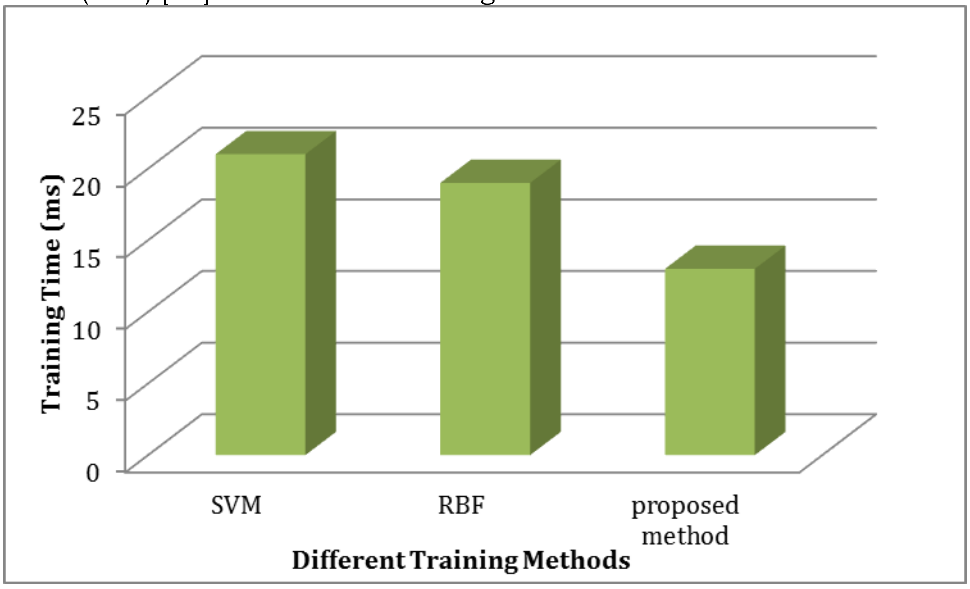

Figure 4: Training Time for Training Methods

The above figure 4 depicted that the proposed Adaboost method effectively trains the extracted features with minimum time when compared to the other training methods. In addition, the training method ensures the high accuracy that shows that the proposed method selects the correct feature while matching process. Then the accuracy of the training process is shown in the figure 5.

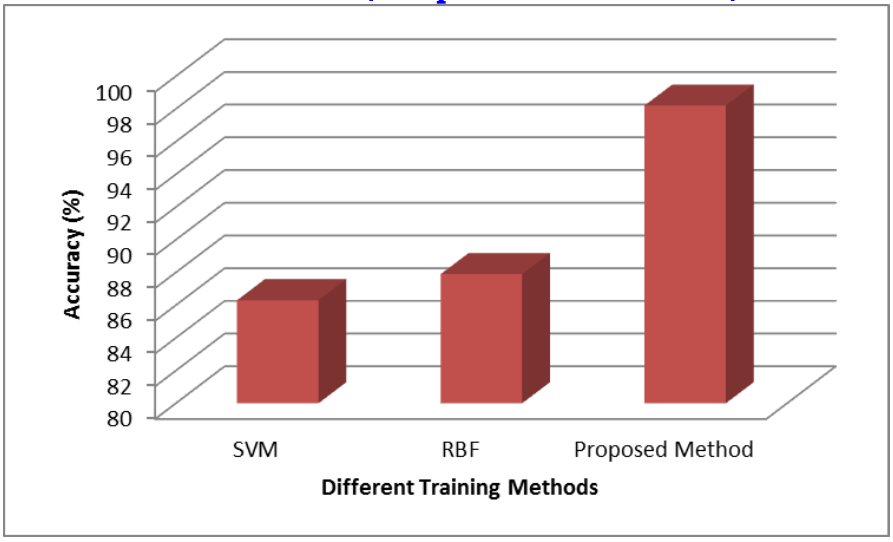

Figure 5: Accuracy of the Different Training Methods

The above figure 5 depicted that the proposed method successfully train the feature with effective manner and the trained features are stored in the database in terms of the template. Then the Adaboost method based trained features are matched with the testing features using the deep neural networks which consumes the minimum error rate when compared to the traditional methods such as K-Nearest Neighbor (KNN) [23], Neural Networks (NN) [24], Back propagation Neural Network (BPN) [25] which is shown in figure 6.

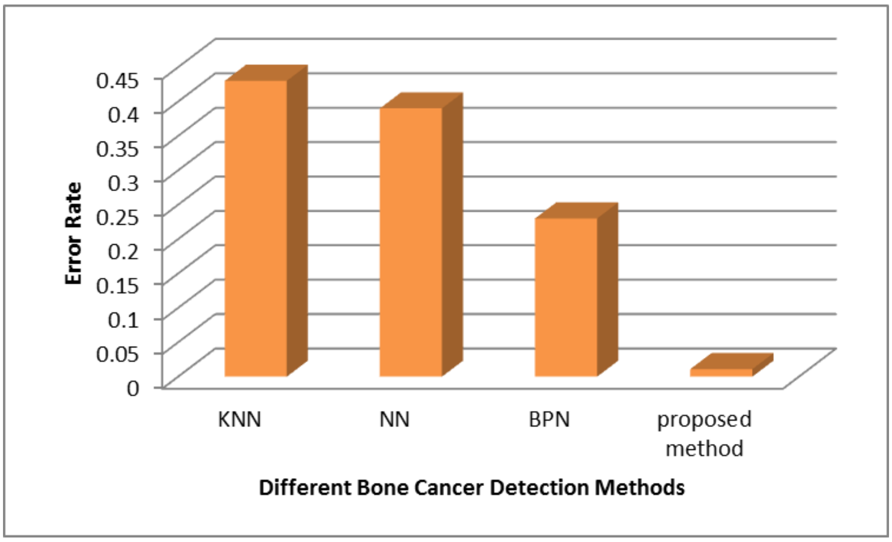

Figure 6: Performance of the Means Square Error Rate

Thus the above figure clearly shows that the proposed method consumes the minimum error rate while classifying the bone cancer related features. This minimized error rate increased the classification accuracy which is shown in figure 7.

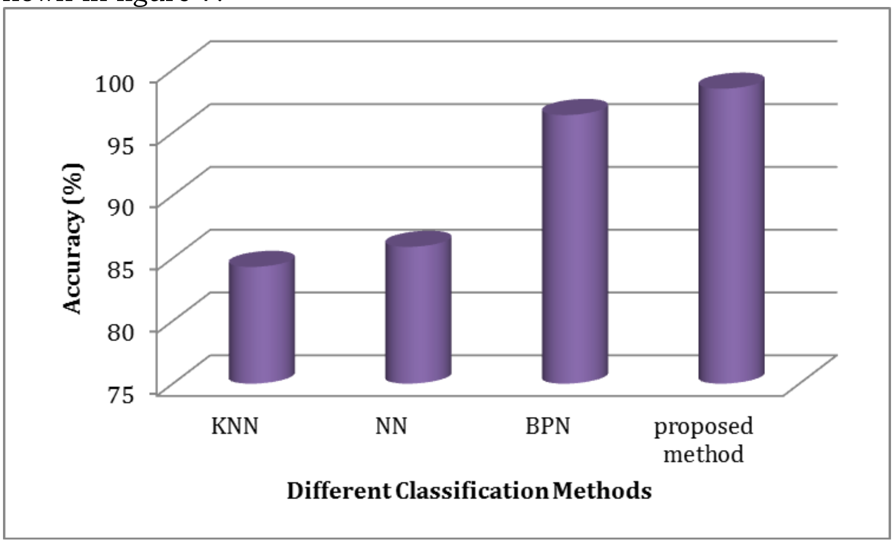

Figure 7: Performance of the Accuracy

Thus the proposed system successfully recognizes the bone cancer features from the extracted features with 99.19% accuracy when compared to the other traditional methods due to the minimum error rate also the effective region segmentation method. Thus the efficiency of the proposed method well worked in the image medical database. Also the proposed Adaboost trained deep machine neural network ensures the high accuracy while classifying the bone cancer features with effective manner.

5. Conclusion:

This paper examining the bone cancer by using the Open-Access Medical Image Repositories dataset with the help of the intuitionistic fuzzy rank correlation along with deep neural networks. Initially the images are collected from the dataset; noise has been eliminated with the help of the median filter. After that the affected regions are analyzed by forming the intuitionistic fuzzy set and the relation between the pixels are examined using the rank correlation process. According to the rank affected regions are clustered and statistical features are extracted which are trained by Adaboost algorithm. Then the new testing features are compared with trained features in the concept of deep neural networks. According to the concept of network, the sigmoid activation function is utilized for recognizing the features with effective manner. Then the effectiveness of the system is evaluated with the help of the medical image dataset. Thus the proposed system ensures the high accuracy while recognizing the bone cancer due to the minimum error rate along with the effective mathematical based segmentation process.

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