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AN EFFICIENT BRITWARI TECHNIQUE TO ENHANCE CANNY EDGE DETECTION ALGORITHM USING DEEP LEARNING

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Abstract

Artificial Intelligence edge detection refers to a set of mathematical techniques used to recognize digital image locations. The picture brightness plays a vital role in detecting dissimilarities and making decisions. Edges are the sharp changes in pictures with respect to the brightness and are commonly categorized into a collection of curved line segments. The main focus of this paper is to find sharp corner edges and the false edges present in the MRI images. The canny edge algorithm is a popular method for detecting these types of edges. The traditional canny edge detection technique has various issues that are discussed in this paper. This study analyses the canny edge algorithm and enhances the smoothing filter, pixel identifier, and feature selection. The proposed Britwari technique, Tabu Search Heuristic Pattern Identifier (TSHPI) enhances the edge detection using SUSAN Filter. Feature Selection is performed to improvise the canny edge method. Deep Learning algorithm is used for classification of pre-trained neural networks to find a greater number of edge pixels. The implementation results show that the Britwari proposed technique (SUSAN Filter Tabu Search Heuristic Pattern Identifier Hill Climbing) reached better accuracy than the traditional Canny Edge Detection algorithms. The results produced better feature set selection using edge detection in MRI images.

Keywords:

Britwari Technique, Edge Detection, Deep Learning, Image Processing

1. INTRODUCTION

The use of Artificial Intelligence (AI) allows Computers to perform functions that were traditionally done by humans. The process consists of creating algorithms for classifying, analysing, and making predictions based on data. It also involves discovering new information and improving them over time. Deep Learning (DL) is the next advancement of Machine Learning (ML). Deep learning is capable of learning from both structured and unlabelled inputs. It is used for edge detection, image classification, picture restoration, object recognition, and image segmentation. It is a proven that DL has yielded astonishingly accurate results. Multilayer perceptron (MLP), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) are some of the important techniques that are used in deep learning networks.

To handle the AI edge detection challenge, Deep Learning approach uses Convolutional Neural Networks. The CNN method is very simple to adapt and is combined into people's individual computer vision task. Many research and implementations are being made to include CNN in every aspect of DL computer vision. The paper describes the all components, important parameters of CNN and how they work. It also outlines the parameters that affect CNN performance [1]. Concerning AI Machine Learning, CNN performs more effectively. In most of the research work, CNN deals with the image data to identify the edges along with the Natural Language Processing (NLP). Trained Convolutional Neural Networks identify edges from picture regions directly. This work is extract unnecessary feature processes, simple, and fast without loses detection accuracy by using such networks [2]. The standard edge detection approaches are described in this paper.

By the use of MATLAB software, numerous edge detection approaches are tested in many images. As a result, it is found that canny edge detection produces satisfactory accuracy rate.

It has reduced irrelevant pixels, and minimized computationally expensive operations in comparison to standard algorithms [3]. An approach for detecting edges is the Convolutional Neural Network. It has to be trained appropriately with a variety of edges and non-edge structures so as to make it more efficient in identifying any test image [4]. The CNN technique is used to detect edges on roof photos. Because of the edge detection challenge, the overall method is great, quick, and reliable to operate. Furthermore, without any extra training or dimensionality reduction CNN can manage any sized image as input [5]. To identify pixels in a convolutional neural network, the convolution kernel technique is used to detect the edges. There's not a precise method for edge detection to extract the data for several years. The author, enhanced edge detection to extract the data [6].

2. RELATED WORKS

This study proposes a quick implementation of the SUSAN edge detector to reduce redundancy. This research made proved that the proposed solution is efficient than existing techniques. The proposed work speeds up the SUSAN filter edge detection while preserving its detection accuracy [7]. The proposed SUSAN methodology focused on the images localized with grey value features and with sensitivity and edge detection. The enhanced SUSAN filter outperformed the conventional Gaussian filter and salt-and-pepper noise method. In fact, the enhanced SUSAN outperforms all of the detection analysed for noisy data such as salt-and-pepper [8]. The proposed methodology developed in this study has the ability to increase low-level vision performance and outperforms edge detecting canny approach [9]. The online performance testing of the pantograph slide plate is proposed in this research using an innovative and intelligent method based on deep learning and image processing technologies. The results of the experiments demonstrated that the novel PDDNet accurately detects surface structure defects and classified four types of defects. The proposed method achieves good estimation accuracy when the wear image retrieval findings are compared to on-site data measured. PDDNet enhances accuracy by 6.25 % when compared to AlexNet's optimization accuracy [10]. The proposed SUSAN method is an enhanced corner detector, which acts as an excellent approach for detecting corners in dental images. It provides accurate values for three-dimensional restoration [11]. The new interpretation is based on the diagonally weighted regression which to relates SUSAN filter to a box sliding across the surface of an image. The proposed SUSAN filter enhances thinner edges without the need for an additional thinning step while preserving all other benefits [12]

The methodology is a deep learning-based edge detection approach for cancer images. To find the location of the cancer, a linear fusion model was created for the images and RGB image feature matching approaches are applied. The proposed technique improved the accuracy of the three-dimensional pictures and the identification of optimum values. The proposed approach is more accurate in detecting cancer images, has greater feature resolution, and is more practical [13]. This method of brain tumor segmentation saves a surgeon time and provides greater accuracy. To segment out the tumor, it is important to exclude any parts of the brain. The morphological operation and region growing segmentation both are methods demonstrated with successful outcomes [14]. Proposed technique was used to a better region-based CNN and edge detection method in image processing techniques to identify glioma cells in MRI. The work used for tumour mask to identified the region of interest that glioma cells and detected the tumour on MRI with high certainty [15]. Firstly, deep convolutional neural networks (DCNNs) were used as classifiers. The second step involves detecting tumor regions of interest, using a region-based convolutional neural network (R-CNN). During the final phase of the segmentation process, the concentrated tumor boundary was contoured using the Chan-Vese segmentation algorithm. Performance of the proposed architecture was high for both glioma segmentation and meningioma segmentation [16].

3. METHODOLOGY

The AI system which operates on the edge application platform, object detects and edge predicts safety procedures. In image processing, edge detection is used for discovering knowledge and image classification. Object detection, visual saliency detection, monitoring, and motion analysis, structure from action, video processing, automated driving, and imagery to text analysis of many other applications use edge detection. Finding edge points and determining the brightness of discontinuities is called edge detection. The proposed method is an enhancement for canny edge detection which is a several-step technique for detecting edges while suppressing noise.

The canny process is used to decrease noise, unnecessary features and texture, by using a Gaussian filter to process images. The canny algorithm is really good for detecting edges and reducing noises. Existing canny approach detects the joint connections and corner edges which results in not so accurate clear edges. The junction connections and finding corner edges were issues for the canny method: Canny method is blurred by the Gaussian filter smoothing, making features more difficult to identify an edge. This proposed work finds corner edge pixels values, scanning in the wrong direction, missing neighbouring values, and it gives good accuracy.

3.1 SUSAN DETECT THE EDGE FILTER

The Noise Removal and Image Pre-processing are used to select the input image data, which can be either an RGB color or gray scale picture. An RGB image, is converted into a gray-scale. It is necessary to smooth the image after it has been captured by decreasing the noise. The image input is also applied with a filter to reduce noise. In this scenario, the Loss function is used to improve the image's edge. The proposed method is firstly introduced with the SUSAN approach. It solves this complicated corner edge locating the problem, giving by better connecting edges and producing good connections when applied SUSAN filters for canny method. This method scans the overall image in pre-processing. This method performed to the CNN classifier makes the detection of edges more accurate. The SUSAN filter helped reduce noise redundancy. Nearby pixels in the circular masks between each pixel in the rectangular scan order are captured and applied determine to reduce corner edge noise. In the SUSAN filter analyzes the pixel region, which is used to identify whether the current pixel value is an edge location or not. Image noise removal filtering, image edge finding, and corner pixels finding are all covered by the non-linear SUSAN filter. Because it is difficult to identify the corner edges from some specific pixels on the image boundaries using the Gaussian filter, this proposed work aims to improve the drawback of SUSAN filter. It uses a SUSAN filter to extract probable corners in image edges.

3.2 TABU SEARCH HEURISTICS SYMMETRICAL PATTERN IDENTIFIER (TSHSPI)

Symmetrical property is one of the prime attributes when dealing with medical images. This symmetrical property has a higher index in the case of MRI images. The proposed model aims to improve symmetrical property to edge detection speed and find edge pixels. A new Tabu search algorithm is introduced in this algorithm to optimize the edge detection process in MRI Images. The key of this meta-heuristic optimization lies on the selection of symmetrical edges from an MRI image in different directions. This process begins with finding the center of an MRI Image. The proposed TSHSPI technique improves accuracy, performance, speed, and efficiency. This method is used to evaluate and choose the best pixels in pattern identifier for which gradient edge direction is calculated. An illustration in Figure 1 is given for ease of understanding the Tabu Solution Set Formation Algorithm.

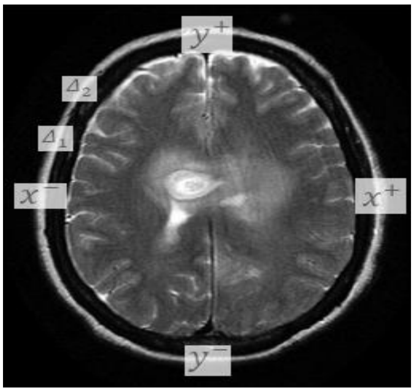

Fig.1. Point's/Element positions

Algorithm: Tabu Solution Set Formation:

Understanding the Tabu Solution Set Formation Algorithm:

Input: MRI Image

Output: Tabu Solution Set

Step 1: Find x^- which is the left most edge point of an MRI image

Step 2: Find x^+ which is the right most edge point

Step 3: Similarly find y^- and y^+ in the vertical direction

Step 4: Calculate the center point of image c_i as

$$(\{0.5(x^++x^-)\},\{0.5(y^++y^-)\}) \tag{1}$$

Step 5: Let A_v and A_h are the virtual vertical and horizontal axis intersect in the point c_i

Step 6: Label edge positions from y^- to x^- through path y^+, x^+, y^- for every 22.5° as $\{\Delta_0,\Delta_1\ldots\Delta_{15}\}\in D$

Step 7: Set D will be the initial solution set of Tabu search

3.3 CANNY METHOD USING EDGE EXTRACTION

Canny edge detection is a technique for extracting relevant structural information from various image features while reducing the number of data to be processed significantly. Canny edge detection is used to find the edges from the MRI Images and their results will be labelled separately for successive functional modules. Canny edge detection is extracting the strong edge pixels should certainly be involved in the final edge image, as they are extracted from the true edges in the image. There will be some contention over the weak edge pixels, which can be taken from the true edge or the noise or color changes. These poor edges created by the worst issues for blur images should be eliminated to obtain accurate results. A weak edge image resulting from real image edges is usually related to a powerful edge point, while noise replies are absent. An edge connection is detected by looking at the neighbors of a weak edge pixel. Any weak edge point in the blob is identified as a point to preserve it if it is involved in one strong edge pixel. Then the canny feature extraction method tracks the edges which cause edge thinning. Finally, this process is used for extract the MRI image edges.

3.4 FEATURE SELECTION

Hill Climbing is a heuristic search technique used in the field of Machine Learning to solve mathematical optimizing challenges. Hill Climbing feature selection is referred to the process of selecting the subset of features for constructing a model in machine learning and statistics, as well as selecting a variety of attributes. The aim of feature selection methods is to decrease the number of input data points to those that will be most benefit in predicting the target pixel data points. A machine learning model is built automatically by selecting relevant features according to the type of problem it is trying to solve. Feature selection process of including or removing essential pixels without altering them. This reduces the amount of noise in data and decreases the size of input data. The purpose of the proposed work is to select features and to remove redundant or uninformative pixel predictors from the model. Then features selected are used in classification to select a set of highly identifying features. In other words, it selects features that are capable of identifying samples that belong to different pixels. So, given a huge set of input image data and a good heuristic value, the algorithm aims to discover the optimal solution to the edge detection issues in the shortest period of time.

3.5 CLASSIFICATION OF PRE-PROCESSING IMAGES FOR CNN

Edge detection tasks are the focus of this proposed work used for the classification of the pre-processing images to the CNN approach. It implements feature extraction and can handle any image as input of any size without the need for further pre-or post-processing training. A CNN is the prime classifier which is implemented. The CNN classified for MRI images to detect the pixel location. The convolution operation is calculated first, and then the convolution layers are linked with a sub-sampling layer.

It reduces calculation time and improves the efficiency of finding correct pixel values. The input receives pre-processed images, and every layer takes inputs from a small neighbour pixels region of units.

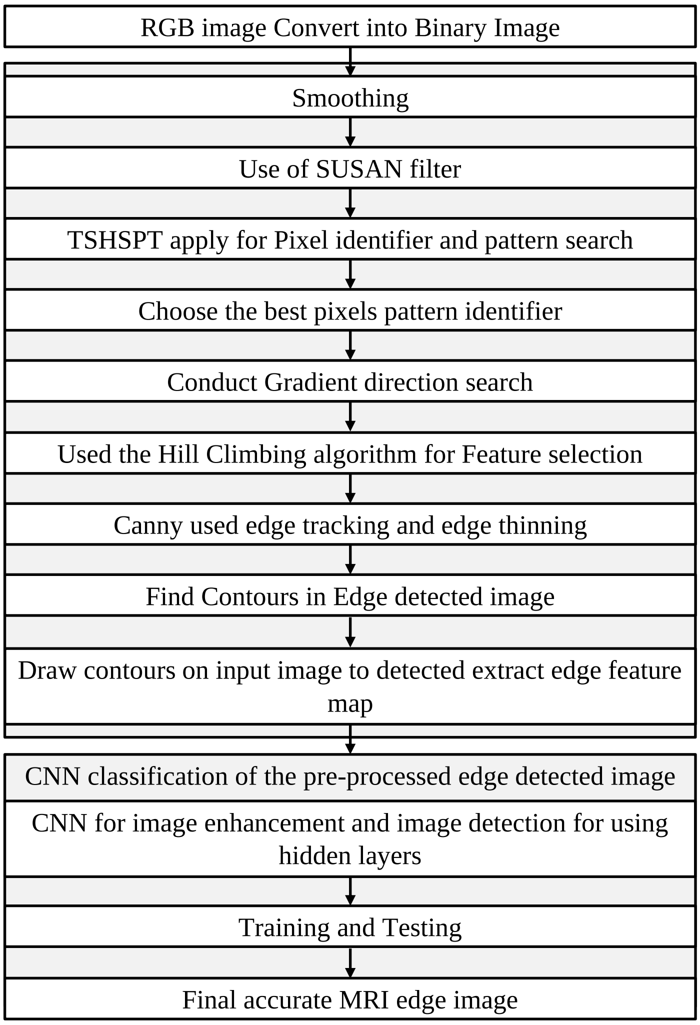

Fig.2. Proposed Methodology

The convolutional layer is used to transfer input images into output images by using edge detection kernel filtering. The kernel filter scans an image and develops a few pixels at the time a feature map that eliminates irrelevant features. To identify an edge in a grey scale image, first, apply a 3×3 matrix known as a filter or kernel. Then, convolve the 6×6 or 5×5 images with the

3×3 filter to get 4×4 or 3×3 images as results. After that, the filter is moved to a different edge position, and the convolutional operation is repeated until all Pixels value are obtained. Convolution is the multiplication and addition of two matrices, in the two regions patches matching of kernel's rows and columns (the kernel and the image matrix). The CNN filters take picture regions as input data and predict whether or not the middle pixels of those regions are on the edge. This process is used in the pooling layer after a convolution layer to decrease extracted input data. After performing convolution on the image, add ReLU activation to the matrices. Pool the data to minimize size of the dimensionality. Until satisfied add as many convolutional layer and pooling layers. The CNN, neuron along with its weights and biases creates the Fully Connected (FC) layer. The neurons between the two layers are connected with help of the FC layer. The flatten layer output data is fed into the FC layer input. Fully connected layers are analysed, and then predicted to give the best result. This proposed technique is used to analyse the maximum true and corner edges. After training and testing, a picture results in a more accurate edges, measures the true edges and detects corner edges. All these are approaches involved in the proposed work.

4. RESULTS AND DISCUSSION

To compare the overall performances of existing approaches and the proposed Britwari technique, the tests are conducted by combining the dataset into separate chunks. To achieve a thorough overview, all techniques in each time chunk are measured for Accuracy, Precision, Sensitivity, Specificity, and F-Score.

4.1 ACCURACY

Any classifier method's accuracy is some of the most important evaluation factors.

Table.1. Accuracy of Proposed Britwari technique

Parameter	DLAC	EDACL	MGSDL	TDIP	Britwari
10	94.95	89.47	95.28	93.35	98.10
20	94.86	94.86	95.39	93.92	98.17
30	95.33	89.85	95.53	93.69	98.43
40	95.15	90.33	95.76	93.58	98.45
50	93.52	90.67	95.63	93.83	98.58
60	95.36	90.17	96.10	94.05	98.58
70	95.36	90.17	96.10	94.05	98.58
80	95.58	90.56	96.28	94.02	98.02
90	95.75	90.52	96.45	94.27	98.77
100	95.46	90.65	96.20	94.11	98.98

$$Accuracy = (TP+TN)/(TP+FP+FN+TN), \quad (2)$$

where True Positive, True Negative, False Positive, and False Negative, accuracy is computed. The accuracy of classifiers is related to their efficiency and accuracy values that have been measured for existing. The proposed work achieved the highest accuracy average of 98.98% and placed first. MGSDL is in second place, with an average accuracy of 96.45%.

4.2 SPECIFICITY

The accuracy of a classification approach to find negative outcomes is referred to as specificity, also known as True Negative rate. In classification and machine learning approaches, specificity is given equal weight. According to the findings, the proposed Britwari technique classification method has the greatest Specificity Value of 98.62%. Britwari has the minimum predicted value of 97.51 %, which is greater than the greatest seen rates of other approaches.

Table.2. Proposed Britwari technique Specificity

Parameter	DLAC	EDACL	MGSDL	TDIP	Britwari
10	95.10	89.44	95.34	93.65	97.51
20	94.82	90.21	95.30	93.97	98.02
30	95.21	89.72	95.59	93.48	98.02
40	94.91	90.23	95.93	93.48	98.24
50	95.40	90.63	95.54	93.88	98.43
60	95.78	90.09	95.78	94.04	98.58
70	95.43	90.24	95.93	94.09	98.39
80	95.42	90.49	96.38	93.99	98.53
90	95.86	90.72	96.36	94.43	98.65
100	95.42	90.44	96.07	94.23	98.62

4.3 PRECISION

The precision is measured as both the quantity of correctly identified Positive samples to the total number of Pixels samples.

$$\text{Precision} = TP/(TP+FP) \quad (3)$$

The precision of the model in classifying a sample as positive is accurately measured. The proposed Briwari work gives highest accuracy precision value of 98.65%.

Table.3. Britwari Precision Result

Parameter	DLAC	EDACL	MGSDL	TDIP	Britwari
10	95.11	89.43	95.34	93.69	97.48
20	94.81	90.21	95.29	93.98	98.01
30	95.20	89.68	95.60	93.45	98.23
40	94.89	90.20	95.95	93.47	98.00
50	95.39	90.62	95.53	93.88	98.42
60	95.78	90.02	95.77	94.04	98.57
70	95.43	90.25	95.91	94.10	98.38
80	95.43	90.47	96.38	93.98	98.52
90	95.87	90.77	96.35	94.45	98.65
100	95.41	90.39	96.06	94.23	98.61

4.4 SENSITIVITY

The model's order to predict positive data points is measured by its sensitivity. The ability of a test to properly identify diseased patients who might have the disease is referred to as sensitivity. The greater the sensitivity, the much more positive samples are discovered. The classified proposed Britwari technique has the greatest sensitivity value of 99.34%, according to the calculated findings. Proposed Britwari technique has the minimum accuracy of 98.32 %, which is greater than the higher seen rates of other approaches.

Table.4. Sensitivity Levels

Parameter	DLAC	EDACL	MGSDL	TDIP	Briwari
10	94.81	89.51	95.22	93.05	98.70
20	94.91	90.22	95.48	93.88	98.32
30	95.45	89.99	95.47	93.90	98.63
40	95.38	90.44	95.58	93.68	98.89
50	95.64	90.70	95.73	93.79	98.73
60	95.49	90.63	95.88	94.10	98.64
70	95.29	90.11	96.27	94.00	98.78
80	95.74	90.63	96.18	94.04	98.92
90	95.65	90.32	96.54	94.12	98.88
100	95.51	90.85	96.33	93.99	99.34

4.5 F1-SCORE

Precision and recall are both considered while calculating the F1-Score. It's the recall and precision mean average.

F1-Score = 2*(*Recall* * *Precision*) / (*Recall* + *Precision*) (4)

When the F1-Score for the approaches is calculated, Briwari has the best amount of 98.57%. Proposed Britwari technique has the smaller score of 90.70. As a result, it's clear that Briwari -F1 Score, ranking is superior to any other approaches.

Table.5. F1 Score values

Parameter	DLAC	EDACL	MGSDL	TDIP	Britwari
10	94.96	89.47	95.28	93.37	98.08
20	94.96	90.22	95.39	93.93	98.17
30	95.33	89.84	95.53	93.67	98.43
40	95.13	90.32	95.77	93.57	98.45
50	95.64	90.70	95.73	93.79	98.73
60	95.64	90.33	95.83	94.07	98.61
70	95.36	90.55	96.28	94.01	98.72
80	95.57	90.55	96.28	94.01	98.97
90	95.76	90.55	96.44	94.28	98.77
100	95.46	90.62	96.19	94.11	98.97

5. CONCLUSION

In this work, deep learning technology is used to increase the accuracy of edge detection problems. It is used to find false, true edges and corner edges using the proposed Britwari model. This proposed work is implemented using VC++. The pre-trained neural network is used to identify more edge pixel values using a proposed method for Britwari. CNN is used to enhance the MRI images by using hidden layers in predicting edges from picture patches directly. By using such systems irrelevant information can be reduced, extra features are extracted, features are selected in a way to make the system efficient without losing image quality. This proposed edge detection approach increases the edge efficiency when more edges are detected. Based on the accuracy of proposed method, it is found to be the best when compared with existing edge detection methods. The experimental results demonstrate that the enhanced canny algorithm is more adjustable, can filter noise effectively, reduce false detection rates, and produce a sharper detected picture shape.

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