International Journal On Engineering Technology and Sciences – IJETS
ISSN(P): 2349-3968, ISSN (O): 2349-3976
Volume VI, Issue V, May - 2019

Automatic Detection Of Tumor Using DBN via Super Resolution Images

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ABSTRACT
A Novel approach for detecting brain tumor from very deep super resolution MRI (Magnetic Resonance Images) images using deep belief networks. Super resolution images have many applications like medical imaging, video surveillance, astronomy. In medical imaging increase the resolution of medical images should also improve the ability of treatment so it make helps to physicians to determine, diagnose also provide correct treatment for disease. Therefore high resolution may substantially improve automatic detection and image segmentation. Resolution of medical image depends on imaging environments, physical constrains and also quality limiting factors such as noise. A very deep convolutional network layers used to increase the resolution accurately better than others. This image super resolution architecture is very deep convolutional network having 20 layers of convolution. First layer operates on input image and the last layer for the image reconstruction. Using these super resolution images can apply different image processing technique such as image segmentation, image classification and feature extraction. Further here propose a brain tumour detection technique using deep belief network. This super resolution image is applied to a tumor detection method based on deep belief network. This super resolution technique along with deep belief network based classification provide more accuracy in results.

Index Terms: Medical Imaging, super Resolution, Very Deep Super Resolution, Tumor Detection, Deep Belief Network.

1. INTRODUCTION

Medical imaging also known as diagnostic imaging, through this doctors look your body for knowing about a medical condition. A variety of machines and techniques can create pictures of the structures and activities inside your body. The type of imaging your doctor uses depends on your symptoms and the part of your body being examined. They include X-rays, CT scans, Nuclear medicine scans, MRI scans Ultrasound. Many imaging tests are painless and easy depend on equipment and related disease. Some require you to stay still for a long time inside a machine. This can be uncomfortable. Certain tests involve exposure to a small amount of radiation. Widely used in patient analysis and medical diagnosis, MRI often reveals different information about bodily structures than can be visualized using other imaging methods such as X-ray, computed tomography (CT) or ultrasound [1]. Medical imaging is an important diagnosis instrument to determine the presence of certain diseases. Therefore increasing the image resolution should significantly improve the diagnosis ability for corrective treatment. Furthermore, a better resolution may substantially improve automatic detection and image segmentation results. This paper provides an method on super-resolution (SR) research in medical imaging and its application in tumor detection. A tumor also known as neoplasm is a growth in the abnormal tissue which can be differentiated from the surrounding tissue by its structure. Great knowledge and experience on radiology are required for accurate tumor detection in medical imaging. Automation of tumor detection is required because there might be a shortage of skilled radiologists at a time of great need.

Machine learning algorithms have the potential to be invested deeply in all fields of medicine, from drug discovery to clinical decision making, significantly altering the way medicine is practiced. The success of machine learning algorithms at computer vision tasks in recent years comes at an opportune time when medical records are increasingly digitalized. Manual are limited by speed, fatigue, and experience. It takes years and great financial cost to train a qualified radiologist, and some health-care systems outsource radiology reporting to lower-cost countries via teleradiology. A delayed or erroneous diagnosis causes harm to the patient. Therefore, it is ideal for medical image analysis to be carried out by an automated, accurate and efficient machine learning algorithm. Deep learning is a branch of machine learning algorithms and aims at learning the hierarchical representation of data. Deep learning has shown prominent superiority over other machine learning algorithms in many artificial intelligence domains, such as computer vision, speech recognition and nature language processing.

The brain is the most important part of the central nervous system. The structure and function of the brain need to be studied noninvasively by doctors and researchers using MRI imaging techniques. More appropriate approaches for estimating the high frequency information are known as super-resolution methods, as they are meant to enhance the spatial resolution. SR has been a well-explored technique in computer vision. Popular methods include neighbor embedding regression, random forest approaches and state-of-the-art CNN methods. Some methods require external paired atlas images to learn the transformation from low (LR) to high resolution (HR). The major benefit of using image processing technique is the time for detection will comparatively much lesser than manual detection. The result of such image processing technique is the tumor is detected and the correct position of the tumor is determined. There also exist many automated diagnostic systems which plays a major role in detection of brain tumors in MR images. Medical imaging has some other goals, such as extract quantitative values from images that would be difficult or impossible to measure directly, for example. Brain volume, or even more difficult to measure directly; brain volume change between two scans. This can be used to perform statistical population analyses. Help the radiologist find suspicious things. Radiologists are very good at interpreting images, but they get tired and can miss things. Algorithms can point them to anything that might be interesting such as lesions, tumors, etc. Assist the radiologist in making difficult choices like lung nodule classification and breast lesion classification. In the near future, in addition to these, will see more and more fully automated interpretation of simple scans, which could be used to complete or even replace the radiologists' interpretation.

2. RELATED WORK

The main objective of super resolution is to determine the high resolution image from either low resolution input or a set of images. Image super resolution is important in many applications [2] like multimedia, medical imaging and video surveillances. The technical disorders from the imaging devices and systems such as optical distortions and lens blur, motion due to speed and presence of noises also cause image degradation. When take the super resolution related works, it can be broadly classified into three categories[3]. The first category is inter polation based method, this is a simplest method like apply interpolation on visual data acquired from sensor [4]. It has some limitations like not possible to obtain the high frequency information in the resized image. Bilinear interpolation and bicubic interpolation methods example for interpolation based method [5-8]. The second category is reconstruction based methods produce high resolution image by applying various prior smoothness [9,10]. Next category is example based method is to estimate the most appropriate alternative high resolution version of a low resolution image from the examples [11]. Chao Dong proposes a deep learning method for single image super resolution. This is end to end mapping between low and high resolution images. The mapping is represented as a deep convolutional network.

There are several methods are for tumor diagnosis or tumor detection. The work done in most recent years by means of machine learning and classification methods. A new hybrid technique based on the support vector machine (SVM) and fuzzy c-means for brain tumor classification is proposed [12]. The purposed algorithm is a combination of support vector machine (SVM) and fuzzy c- means, a hybrid technique for prediction of brain tumor. The enhanced images are fed to a pre-trained convolutional neural network (CNN) which is a member of deep learning models. The CNN classifier, [13] which is trained by large number of training samples, distinguishes between melanoma and benign cases. The tumor detection techniques as DWT and GLCM are used for feature extraction, where textural and intensity base features are drawn by utilizing GLCM and DWT. Different parameters have to measure the resolutions band detection. Peak signal to noise ratio, structural similarity index and mean square error are estimation parameters of super resolution. Accuracy, sensitivity and specificity are the parameters related to tumor detection.

3. METHODOLOGY

Deep learning methods utilizing deep convolutional neural networks have been applied to medical image analysis providing promising results. The application area covers of medical image analysis including detection, segmentation, classification, and computer aided diagnosis. Here first increase the resolution of the input magnetic resonance medical imaging through very deep resolution method or architecture.The output image of super resolution is fed into deep belief network. For this first convert the image into 28*28 pixels of image, because of high number of pixels of image take more time for computation. After this some image preprocessing are done and fed into deep belief network. Deep belief network is composed of stacked restricted Boltzmann machines and lean features using this RBM network. RBM worked based on gradient descent algorithm to minimize the value error with the value set as the threshold. Here set the values as one for the tumor pixel and zero for the non tumor pixel. After attain one of the threshold value some image post processing done and then classify as the tumor brain or healthy brain.

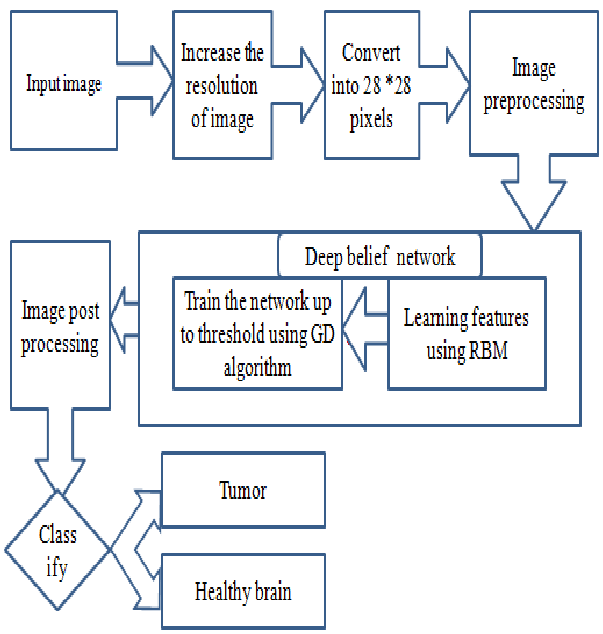

Fig 1 workflow of proposed method

A. VDSR ARCHITECRTURE

VDSR is a 20-layer VGG-net. The VGG architecture sets all kernel size as 3×3 the kernel size is usually an odd, and taken the increasing of receptive field into account, 3 × 3 is the smallest kernel size. To train this deep model, they used a relatively big initial learning rate to accelerate convergence and used gradient clipping to prevent gradient explosion problem. Besides this architecture, VDSR [14] has made two other contributions. The first one is that a single model is used for multiple scales based on the fact that the single image super resolution processes with different scale factors have strong relationship with each other. Like SRCNN, VDSR takes the bicubic of LR as input. During training, VDSR put the bicubics of LR of different scale factors together for training. For larger scale factors (×3, ×4), the mapping for a smaller scale factor (×2) may be also informative. The second contribution is the residual learning. Unlike the direct mapping from the bicubic version to HR, VDSR uses deep CNN mediately to learn the mapping from the bicubic to the residual between the bicubic and HR. They argued that residual learning can improve performance and accuracy for the super resolution.

B. DEEP BELIEF NETWORK

In machine learning belief network (DBN) is a generative graphic model, or alternatively a class of deep neural network in machine learning. Deep belief network is composed of multiple layers of latent variables or hidden units. There have connections between the hidden layers but not between units within each layer. A DBN can learn to probabilistically reconstruct its inputs when trained on a set of examples. The layers then act as feature detectors after this learning step, a DBN can be further trained with supervision to perform classification. Professor Geoffrey Hinton introduced Deep Belief Network to overcome the limitations of earlier neural networks. Restricted Boltzmann Machines and Belief Networks are the two different types deep belief network. DBNs can be viewed as a composition of simple, unsupervised networks such as restricted Boltzmann machine (RBMs) or autoencoders, where each sub-network's hidden layer serves as the visible layer for the next layer. An RBM is an undirected, generative energy-based model with a "visible" input layer and a hidden layer and connections between but not within layers. This composition leads to a fast, layer-by-layer unsupervised training procedure, where contrastive divergence is applied to each sub-network in turn, starting from the "lowest" pair of layers. The observation that DBNs can be trained greedily, one layer at a time, led to one of the first effective deep learning algorithms. Overall, there are many attractive implementations and uses of DBNs in real-life applications and scenarios[15].

C. ESTIMATION PARAMETERS

The evaluation metrics used for super resolution and deep belief based detection or tumor detection is different. Peak signal to noise ratio, structural similarity index and mean square error are the evaluation metrics related to image super resolution. Evaluation metrics related to tumor detection are accuracy, sensitivity and specificity. PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of

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its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the lgarithmetic decibel scale. Structural similarity is the index is a method for predicting the perceived quality of digital television and cinematic pictures, as well as other kinds of digital images and videos. Mean square error is the measures the averege of the squares of the errors that is, the average squared difference between the estimated values and what is estimated. Before the estimation of accuracy, sensitivity and specificity some teams also defined. TP be the number of pixels correctly identified as tumor. FP is known as False Positive, it is the number of pixels incorrectly identified as tumor . Next TN is True Negative is the number of pixels correctly identified as healthy and FN that is False Negative means number of pixels incorrectly identified as healthy.

i. Peak signal to noise ratio PSNR=10 $\log_{10}\frac{MAX^2}{MSE}$

ii. Mean square error MSE = $\frac{1}{mn}\sum_0\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j)-K(i,j)]^2$

iii. Structural similarity SSIM(x,y) = $[l((x,y)^{\alpha}.c(x,y)^{\alpha}.s\,(x,y)^{\alpha}]$

iv. Sensitivity TP/ (TP +FN)

v. Specificity TN/ (TN +FP)

vi. Accuracy $\frac{TP+TN}{(TP+TN+FP+FN)}$

D RESULT AND DISCUSSION

The performance and results evaluated below. High resolution or super resolution of input image through bicubic interpolation and corresponding very deep super resolution architecture is depicted in Figure 4.2 and 4.3.

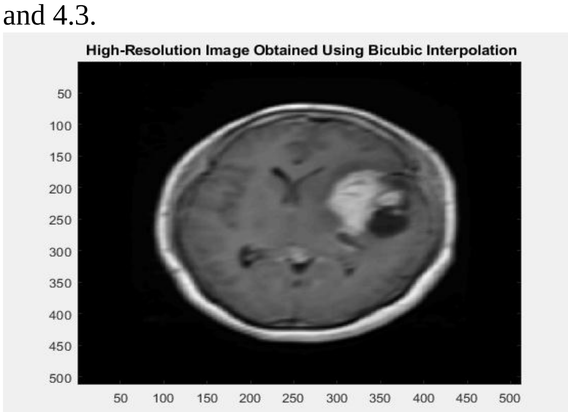

Figure 4.2 High resolution Output image of Bicubic interpolation method

When compare the evaluation metrics of these images can infer the difference in values. The result shows that PSNR for the bicubic interpolation is 53.4464. In that time the PSNR for the very deep super resolution architecture will be 56.892

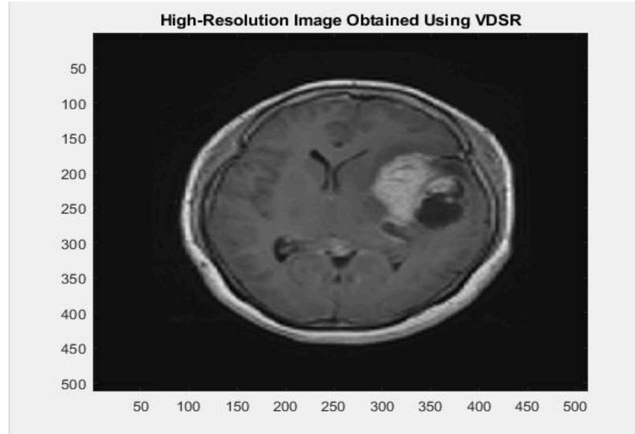

Figure 4.3 High resolution Output image of VDSR method

In addition when compare the other parameters like mean square error and structural similarity the better result is found in very deep super resolution architecture. SSIM and MSE for bicubic interpolation is 0.9939 and 0.0194. The corresponding results of VDSR values will be 0.9972 and 0.008785.

Table 4.1 PSNR, SSIM and MSE comparison on different images for both VDSR and bicubic interpolation method

	PSNR VDSR	PSNR Bicubic	SSIM VDSR	SSIM Bicubic	MSE VDSR	MSC Bicubic
Image 1	54.47	51.63	0.9958	0.9915	0.0153	0.0294
Image 2	55.30	51.90	0.9963	0.9917	0.0126	0.0276
Image 3	57.00	53.41	0.9974	0.9939	0.0085	0.0195
Image 4	56.54	53.34	0.9972	0.9941	0.0095	0.0198
Image 5	65.96	62.46	0.9943	0.9937	0.0024	0.0108
Image 6	63.15	59.00	0.9939	0.9923	0.0019	0.0096

International Journal On Engineering Technology and Sciences – IJETS
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From the table PSNR values of VDSR method of the different images are higher than that of PSNR values of bicubic interpolation method.

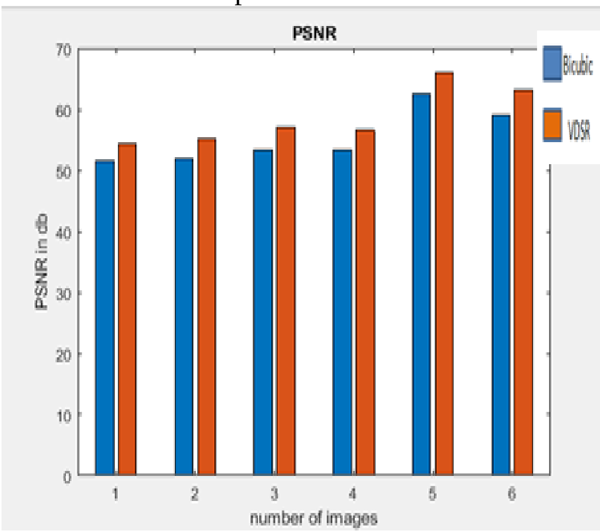

Figure 4.4 PSNR comparison between bicubic and VDSR on different images

MSE be the measurement of error, so it should be low for the VDSR method. SSIM is also high for VDSR method, different images results shows that of less for bicubic interpolation.

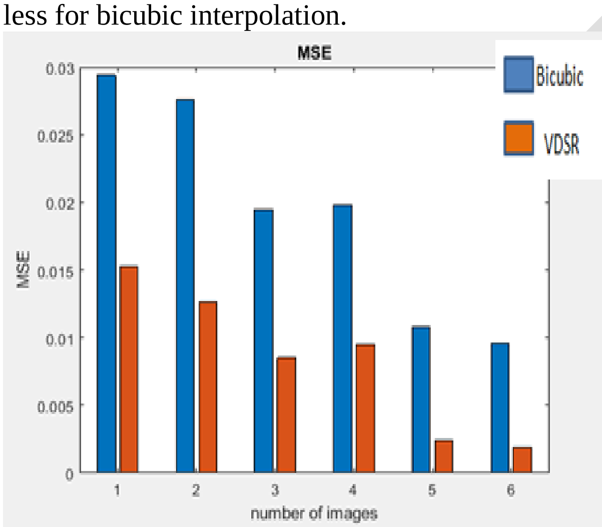

Figure 4.5 MSE comparison between bicubic and VDSR on different images

Figure 4.5 and 4.6 shows the comparison graph between mean square error and structural similarity of bicubic interpolation method and very deep super resolution method. In this graph blue colour describes the effect of bicubic interpolation method and red colour represents VDSR method. 6The SSIM difference of method is comparatively too small, therefore n great difference in bar graph, s chose the point graph.

Sensitivity VDSR +DBN	Sensitivity SVM	Specificity VDSR+ DBN	Specificity SVM	Accuracy VDSR+DBN	Accuracy SVM	Sensitivity VDSR+ DBN
Image 1	0.8791	0.5992	0.9983	0.9971	95.24	59.92
Image 2	0.9332	0.7833	0.9957	0.9942	92.55	78.33
Image 3	0.9824	0.9237	0.9991	0.9982	88.90	25.76
Image 4	0.8479	0.8229	0.9997	0.9985	90.07	82.29
Image 5	0.9239	0.5908	0.9987	0.9974	99.38	56.77
Image 6	0.7525	0.5808	0.9963	0.9949	75.25	58.08

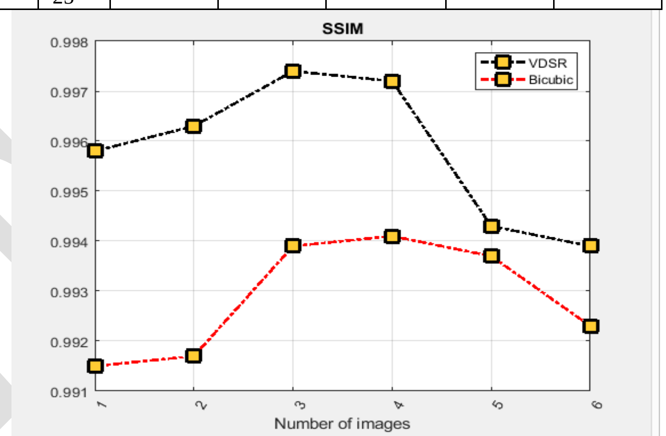

Figure 4.6 SSIM comparison between bicubic and VDSR on different images

The figure 4.8 and 4.9 illustrates the detection accuracy of support vector machine based detection and deep belief based detection. The detection accuracy or area of tumor is high in VDSR +DBN method.

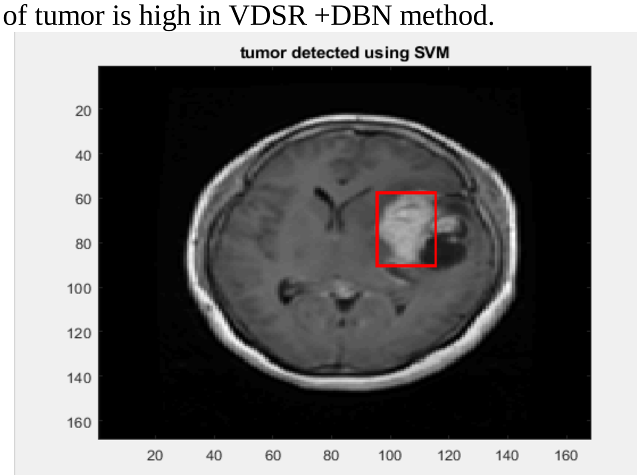

Figure 4.8 Tumor detection using SVM

International Journal On Engineering Technology and Sciences – IJETS
ISSN(P): 2349-3968, ISSN (O): 2349-3976
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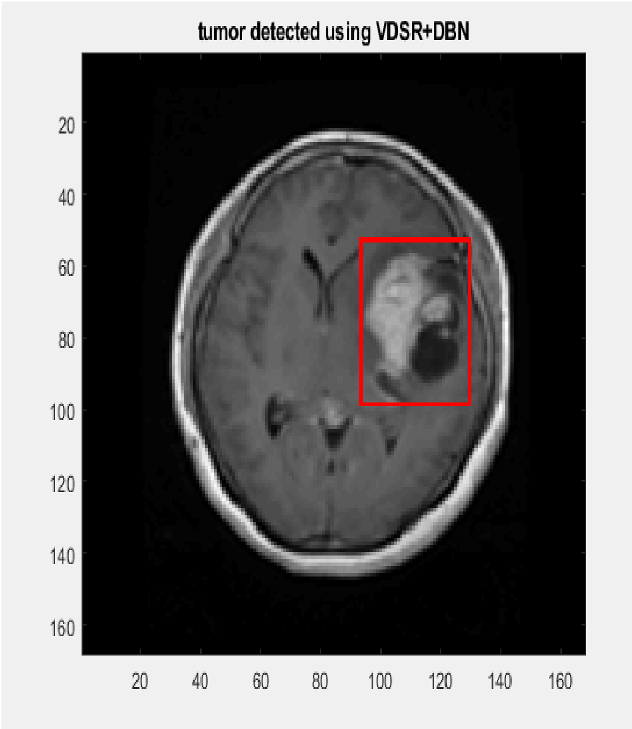

Figure 4.9 Tumor detection using VDSR+DBN

Sensitivity is the ability to determine tumor pixels correctly and specificity is the ability to determine non tumor pixels correctly. Accuracy is the ability to differentiate tumor and healthy brain correctly. For the calculations of this metrics following terms are observed. For the detailed evaluations chart these parameters of different brain tumor images as tabular columns and examine the both support vector machine detection and deep belief network based detection. TP- True Positive: number of pixels correctly identified as tumor . FP- False Positive: number of pixels incorrectly identified as tumor. TN- True Negative: number of pixels correctly identified as healthy .FN- False Negative: number of pixels incorrectly identified as healthy.

Table 4.2 Sensitivity, Specificity and accuracy comparison on different images for both SVM and VDSR+ DBN method

Table 4.2 illustrates the difference between the SVM and VDSR+DBN on the metrics like specificity, sensitivity and accuracy. Here take 6 different brain tumor images from the dataset for the testing. From all images the values regarding sensitivity, specificity and accuracy is higher for VDSR+DBN method. Hence it proves VDSR+DBN is the better method for the tumor detection

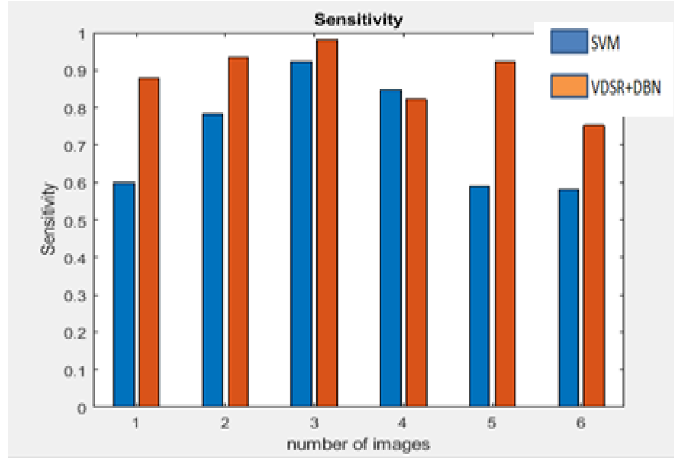

Figure 4.10 Sensitivity comparison between SVM and VDSR+DBN on different images

Figure 4.10 is the graph plotted on the basis of specificity of different images. Here blue indicates the SVM method status and red indicates VDSR+DBN status on th bar graph. Clearly it can inference that VDSR+DBN method is greter performance than SVM based detection. Similarly figure 4.11 is graph plotted between the accurancy of these two methods. In terms of accurancy VDSR+DBN is better method for detection.

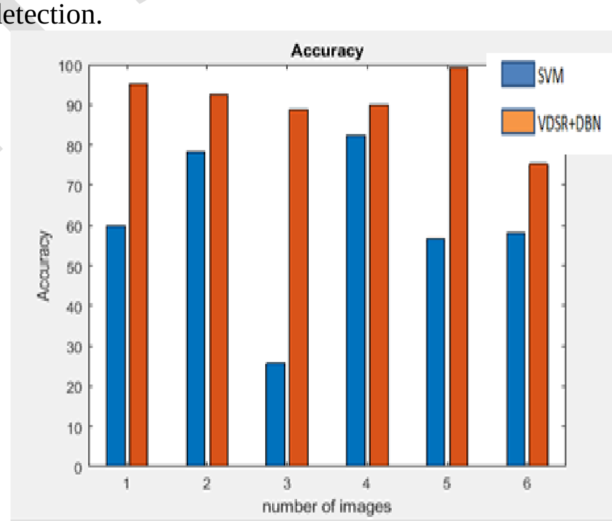

Figure 4.11 Accuracy comparisons between SVM and VDSR+DBN on different images

The values of specificity is lying between 0.0991 to 1, so this is the small differnce to cmpared to all ther evaluation merrics. Therfre no visible differnce in bar graph , it is plotted in point graph on MatlabR18a. Figure 4.12 describes the specificity difference on support vector machine method and deep belief network. From all these graph,when take average for accuracy VDSR+DBN provides 90% accuracy instead of SVM pssess 60% of accuracy.

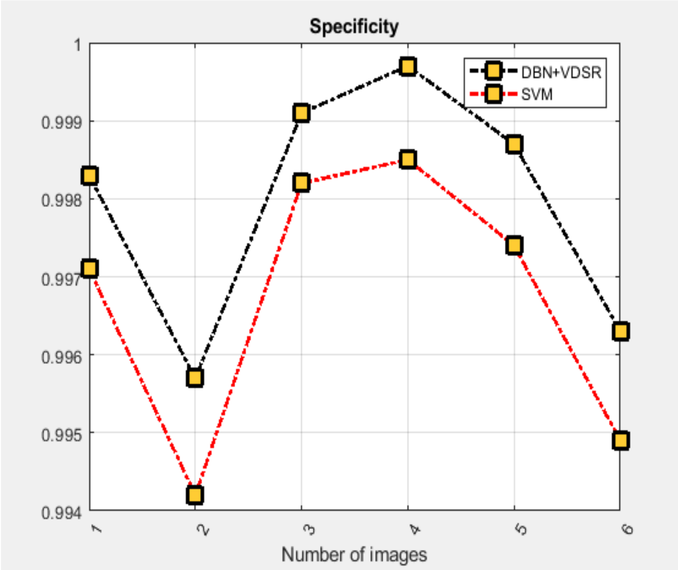

Figure 4.12 Specificity comparison between SVM and VDSR+DBN on different images

4. CONCLUSION

Early detection of cancer greatly increases the chances for successful treatment. The development of technologies capable of early tumor detection is unquestionably demanded by physicians, as early diagnosis is key to achieve more efficient and less invasive treatments with improved outcomes. . A supervised deep convolutional model for super resolution from a source image via deep learning is done. Here use very deep convolutional network for super resolution architecture that increase the resolution of images. The CNN concepts include twenty layers of convolutions including rectified unit Therefore increasing the image resolution should significantly improve the diagnosis ability for corrective treatment. Furthermore, a better resolution may substantially improve automatic detection and image segmentation results. this high resolution images used to detect tumor via deep belief network. A deep belief network is a generative graphic model, A DBN can learn to probabilistically reconstruct its inputs when trained on a set of examples in an unsupervised way. The layers then act as feature detectors on inputs. After this learning step, to perform classification, a DBN can be detect tumr area of the image. The DBN based brain tumor detection algorithm is successfully implemented and applied on dicom images collected from hospitals.

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