

CNN AND HYBRID NEURAL-SVM TECHNIQUE FOR BIOMEDICAL IMAGE ENHANCEMENT

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Abstract

This paper presents an advanced approach to increase the quality of biomedical images based upon a hybrid architecture consisting of a Convolutional neural network (CNN). In the proposed method, we have applied a combination of Genetic algorithm and wavelet as a first step to improve the quality of biomedical images such as MRI, CT, X-ray, PET, and Ultrasound images from different body organs. Noisy and poor quality biomedical images have been a big challenge for doctors during diagnosis for years. Therefore, a CNN approach has been used for image denoising. CNN has a large modeling capacity and remarkable advances in network training and design. Additionally, CNN can be embedded as a modular part of traditional methods, which can be used with greater efficiency. As in CNN, the new image formed at each layer due to convolution is passed to the next layer, so it provides better images than the neural networks and is best suited for structured numerical data. Experimental results show that the proposed technique using Convolutional neural networks provides better quantitative results in terms of structured similarity index (SSIM), mean squared error (MSE), standard deviation, accuracy, sensitivity and beta coefficient. Finally, the comparison of Convolutional neural networks and the hybrid Neural-SVM method is done that indicates the best results of CNN in terms of less computational time.

Keywords: Convolution neural networks (CNN), support vector machine, magnetic resonance imaging (MRI), denoising, and enhancement

Introduction

Even nowadays, due to blurry nature, low contrast, and low distinguish-ability from the surroundings; the biomedical imaging has been a challenge for medical diagnostics. A high-resolution image with interior details is the prime objective of medical imaging (Saad and El-Samie, 2008). The image processing techniques make it feasible; to find outcrucial information from clinical images (Ishak *et al.*, 2008). Most of the images, such as micro-calcifications diagnosis in breast images, tumor detection in brain MRI images, lesions detection in

kidney images, and gall bladder stone detection, every kind of image be it an MRI or CT-Scan or Ultrasound, or X-ray image, etc. suffers from different kinds of noises. Salt and pepper, Gaussian noise etc. distort the different biomedical images; that can be introduced through a recording medium, transmission medium, and quantization errors (Bilcu and Vehvilainen, 2007). Noise reduction is an essential step for any complicated algorithm in computer vision and image processing (Ali *et al.*, 2010). As noise significantly affects the intensity of

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image pixels, so different image enhancement techniques existed in the literature with their own pitfalls (Wang and Zhou, 2006). Earlier image enhancements techniques considered a specific kind of image under study. In the present paper, the proposed method worked well in all types of images for enhancement, so various kinds of Ultrasound, MRI, CT, X-ray and PET images are considered under study.

Various linear and non-linear filters have been proposed time to time for denoising the biomedical images like mean and median filters (Abreu *et al.*, 1996), adaptive median filter (Sawant *et al.*, 1999), generalized morphological filters (Chunhui *et al.*, 1998), homomorphic filters (Runtao and Venetsanopoulos, 2003), wavelet filters (Wang *et al.*, 2005; Karthikeyan and Chandrasekhar, 2011) and vector median filters (Astola *et al.*, 1990), etc. Since, denoising retains the essential features of the image and removes the effects of noise, so image denoising techniques cover a significant portion of literature in image processing (Kaur *et al.*, 2002). In the present paper, a new enhancement approach using a Convolution neural network is proposed as it outperforms other soft computing techniques in terms of object classification, image denoising, image compression, and image deblurring (Liu *et al.*, 2019). As compared to feed-forward neural networks, CNNs have a smaller number of connections and parameters so they can be trained easily by varying their depth and breadth. CNN eliminates the need for manual feature extraction i.e., the features are learned directly by CNN.

Related Work

As soft computing techniques outperform conventional techniques in solving problems that have complicated algorithmic solutions, so various soft computing techniques like Neural networks, SVM, Fuzzy logic, and CNN came into view from time to time. Artificial Neural Network (ANN) and SVM are the soft computing techniques that have various applications because ANN provides better results for large datasets, but SVM provides excellent performance for small input features (Osovsky, 2002; Stanley and Miikkulainen, 2002; Revathy and Amalraj, 2011; Padma and Sukanesh, 2013; Sy Ahmad Ubaidillah *et al.*, 2013; Nandpuru *et al.*, 2014) as proposed by Sy Ahmad Ubaidillah *et al.*, 2013 for prostate, ovarian cancer datasets, breast cancer, and liver cancer datasets.

As state-of-art denoising methods suffer from lack of flexibility and sizeable computational complexity, so CNN gained popularity in recent years. In 2009 Jain (Jain and Seung, 2009) applied

five-layered CNN with sigmoid function for original image denoising. Later Xie (Xie *et al.*, 2012) introduced a sparse stacked denoising auto encoder (SSDA) with the limitation of combining all the optimization data at the end. Subsequently, other CNN techniques with encoders came in to view time to time (Agostinelli *et al.*, 2013). In 2016 Dong *et al.* devised a Super-Resolution CNN that claimed simplicity with a moderate number of filters (Dong *et al.*, 2016). In 2016 various CNN techniques came into existence for denoising images like CNN using wavelets for X-ray images (Kang *et al.*, 2016), encoder-decoder based CNN (Mao *et al.*, 2016), Gaussian denoiser (Zhang *et al.*, 2016) and deep convolution network (Kim *et al.*, 2016). In biomedical imaging also CNN has provided promising results for denoising (Kang *et al.*, 2016; Chen *et al.*, 2017; Dufan *et al.*, 2017). Cascaded CNN provided better denoising than deep convolution and wavelet-based denoising approaches (Dufan *et al.*, 2017) CT images. CNN not only has applications in biomedical imaging but also it offered better image enhancement for thermal as well as infrared images (Choi *et al.*, 2016; Bhattacharya *et al.*, 2018). In 2019 Wuyang *et al.* used CNN for forensic image enhancement where modified CNN is employed for JPEG image enhancement, and denoising is done by cropping layer effectively that leads to significant results benefits using local and global contrast enhancement (Wuyang *et al.*, 2019). Pengju Liu further extended the wavelet-based CNN (Dufan *et al.*, 2017) to the multi-wavelet CNN model to achieve better computational efficiency (Liu *et al.*, 2019).

Proposed Method

In the proposed technique, CNN is used for enhancement purposes. CNN takes into account the local dependency of each pixel to the nearby pixels. CNN's are spatially invariant, which indicates that they can detect the same feature anywhere in the image. For each neuron, CNN only looks at a specific receptive field and reuses that filter for all neurons in that channel. This constraint saves computation and provides better results than other soft computing techniques. The diagram of the proposed method is shown in Figure 1.

Image Data

Image data that has been used under study is various biomedical images of different body organs. The Breast MRI image, Abdomen CT image, Brain MRI and CT image, CT lungs, CT Rectal Image, Hepatic MRI image, Ovary Ultrasound image, Liver Ultrasound image, Pancreas Ultrasound image, and



Figure 1. Schematic diagram of proposed method

Kidney Ultrasound image have been used. The images are collected from UCI-repository, Internet images, and Science-direct images, Post Graduate institute of Medical and Research.

Image Enhancement

As a further step in the previous enhancement method (Khatkar and Kumar, 2018) where wavelet and the genetic algorithm has been used for the enhancement purpose; CNN architecture is used for further enhancement. In the previous paper, Genetic algorithm, in combination with wavelet, was used for augmentation. Although it provides better results in terms of better SSIM and CNR values for the biomedical images, but it does not give good results in the name of the Beta value. Moreover, the fitness function used in the method can be improved for better enhancement of images, which is the foremost requirement for biomedical images. The output of the Genetic algorithm does not provide sharp edges in the images due to the fitness function used, so CNN is applied as the next step for the denoising purpose in the present paper. GA classifies image data into noisy and noiseless pixels that are passed as input to the CNN, so it reduces the considerable effort of CNN and reduced the computational time of the proposed method. In the proposal, initially Shift Invariant Feature Transformation (SIFT), and Principal Component Analysis (PCA) techniques are used as a pre-processing step in the enhancement process. Afterward, the wavelet and Genetic algorithm are applied for biomedical image enhancement, followed by the Convolution neural network technique application. Lastly, a comparison of CNN and Neural-SVM approach is made.

Convolutional Neural Networks

The concept of a Convolutional neural network was put forward by Hubel and Wiesel, and its first implementation was completed in 1980 by Fukushima (Fukushima, 1980). The proposed architecture of CNN consists of the Convolution layer followed by the ReLU activation function. The Convolution kernel is of 3×3 size for feature mapping. The MSE (mean square error) is used as a loss function. As in the present study, the image data is small, so 1-D convolution is used for feature maps. The number, size, and structure parameters of the filter are fixed before the training process. For the p layer is a volume layer, the formula for m layer to achieve convolution is as follows

$$X_o^p = f\{\sum_{i \in p_o} x_i^{p-1} * k_{io}^p + b_o^p\} \quad (1)$$

where X_o^p represents the o feature graph of the convolution layer p, on the right side of the equation, is the feature graph p, on the right side of the equation is the feature graph x_i^{p-1} of the P-1 layer and the o filter k_{io}^p of the m layer to realize convolution and sum, plus the bias. f is an excitation function.

The pool layer retains significant features by fixing the feature map and speeds up the dimension of the feature map output from the convolution layer. The standard way of pooling is the average pooling of the neighbourhood's average value and the maximum pooling of the maximum value. Max pooling has been used for image pixel data in the present architecture, and Min pooling has been used for noisy pixel values. By stacking a series of convolution layers interleaved with non-linearity and pooling layers, CNN is capable of capturing hierarchical representations as powerful image descriptions.

The output layer compresses the input from the other layers and converts the output into the number of classes. The output is then generated through the output layer and is compared to the output layer for error generation. The calculated error is back propagated to update the filter.

Hybrid Neural-SVM

In the present study, the comparison of the hybrid Neural-SVM technique is made with the CNN technique. In the hybrid method, firstly, results from previous steps are passed to SVM, and then results of SVM are given to neural networks.

Support Vector Machine

SVM is a supervised learning technique that classifies the data into two or more classes based on the decision plane. It separates between a set of

items having different class memberships. SVMs can deal with both independent and dependent problems in linear and non-linear cases. In the present study, SVM classifies the data into one of the two classes i.e., noisy and non-noisy. As the asymmetrical noise gets added to different pixels in biomedical images, the Radial basis kernel function is used in the proposed approach. The non-linear hyperplanes separate the image pixels into noisy and non-noisy image pixels. The RBF kernel for two data classes P_1, P_2 is (Chang *et al.*, 2010; Gupta and Tiwari, 2014)

$$K(P_1, P_2) = \exp\left(-\frac{\|P_1 - P_2\|^2}{2\sigma^2}\right) \quad (2)$$

where $\|P_1 - P_2\|$ is the squared Euclidean distance, and σ is a free parameter.

$$K(P_1, P_2) = \exp(-\gamma \|P_1 - P_2\|^2) \quad \text{Where } \gamma = \frac{1}{2\sigma^2} \quad (3)$$

The optimum value of γ leads to better classification results without over fitting of data. The hyper plane diagram for SVM is shown in Figure 2.

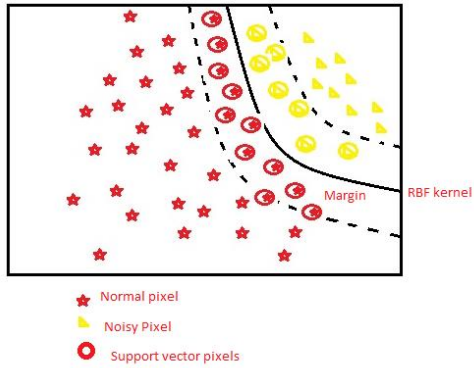


Figure 2. Schematic Diagram of SVM kernel hyper plane

Artificial Neural Networks

The results of SVM are passed to feed-forward back-propagation neural network, which is the supervised learning method that uses a back-propagation algorithm to reduce the error value (Lugina *et al.*, 2005). The back-propagation process from the outer layer to the inner layer leads to the adjustment of weights for the neurons that help ANN to identify and fine-tune the resolving problem. After attaining the information from SVM data, for more accurate results, ANN is used because of its self-learning and self-improving property. According to Larose (Larose, 2005), the number of neurons at the hidden layer should be chosen with great care as too many neurons lead to increment in

computation time while few neurons result in reduced learning ability. In the present study, 100 neurons at the hidden layer are used, and to minimize the error, the weights are restructured after every iteration i.e., the weights resulting in better performance are kept for further processing. Sigmoid activation function is used at the hidden layer as it works equally well for linear, non-linear, and constant behavior input values.

Performance Measures

The identification of noisy or non-noisy pixels in the biomedical images may be erroneous. This error can be evaluated depending on the value of true positive, false positive, true negative, and false negative (Descombes *et al.*, 2004; Ahmmmed *et al.*, 2017). The performance parameters for different biomedical images are as follows.

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \times 100 \quad (4)$$

$$\text{Specificity} = \frac{TN}{(TN+FP)} \times 100 \quad (5)$$

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FN+FP)} \times 100 \quad (6)$$

where, TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative where TP is abnormal pixel correctly identified as abnormal; TN is normal pixel correctly identified as normal; FP is normal pixel incorrectly identified as abnormal and FN is abnormal pixel incorrectly identified as normal.

The SSIM is used to measure the similarity between two images. The SSIM is designed by modelling any image distortion as a combination of three factors that are loss of correlation, luminance distortion and contrast distortion. The SSIM is defined as:

$$SSIM(f, g) = l(f, g) c(f, g) s(f, g) \quad (7)$$

where $l(f, g)$ is the luminance comparison function, which measures the closeness of the two images' mean luminance (μ_f and μ_g). This factor is maximal and equal to 1 only if $\mu_f = \mu_g$. The $c(f, g)$ is the contrast comparison function, which measures the closeness of the contrast of the two images. Here the contrast is measured by the standard deviation σ_f and σ_g . This term is maximal and equal to 1 only if $\sigma_f = \sigma_g$. The $s(f, g)$ is the structure comparison function, which measures the correlation coefficient between the two images f and g . Note that $\sigma_f \sigma_g$ is the covariance between f and g . The positive values of

the SSIM index are in $[0, 1]$. A value of 0 means no correlation between images, and 1 means that $f = g$.

The beta metric is used as an edge preservation measure in the filtered image (Beis and Lowe, 1997)

$$\beta = \frac{r(\Delta I - \bar{\Delta I}, \Delta \hat{I} - \bar{\Delta \hat{I}})}{\sqrt{r(1 - \bar{\Delta I}, \bar{\Delta I}) \cdot r(\Delta \hat{I} - \bar{\Delta \hat{I}}, \Delta \hat{I})}} (I_1, I_2) \sum_{(i,j) \in \text{ROI}} I_1(i, j) \cdot I_2(i, j) \quad (8)$$

where ΔI and $\Delta \hat{I}$ represent the high pass filtered version of the original image $I(i, j)$ and its denoising version $\hat{I}(i, j)$. $\bar{\Delta I}$ and $\bar{\Delta \hat{I}}$ are the mean intensities of ΔI and $\Delta \hat{I}$ respectively. An increasing β indicates a better image quality.

Experimental Results

In this study, the training of the dataset is done in MATLAB framework. For evaluating the performance of the proposed method, the clean biomedical images are used from the UCI repository. The artificial noise, Gaussian white noise is added to the original image with variance

0.6. In the proposed method, the various kind of images like MRI, CT, X-ray, PET, and Ultrasound images are used for different body organs. In the present study, multiple body organ images like Brain, Abdomen, Breast, Liver, Hepatic, Lungs, and Kidney are taken from UCI repository and Science Direct data. The proposed arrangement with the combination of GA and CNN technique results in better performance as compared to other enhancement methods. As GA divides image pixels into noisy and non-noisy pixels and when this data is passed to CNN, it leads to a decrease in computational time. It provides better image quality in terms of SSIM and other metrics used under study.

Standard Evaluation

The evaluation of the proposed technique using CNNs has been done based on different evaluation metrics like SSIM, Hybrid error, sensitivity and specificity. The Figures 3-12 show the denoising of

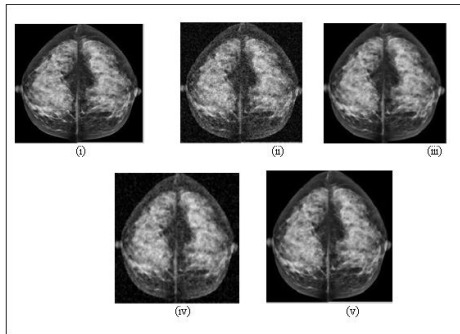


Figure 3. Results of proposed method (I) original image (II) noisy image (III) SYMLET image (IV) CNN Image (V) Neuro-SVM image for Breast MRI

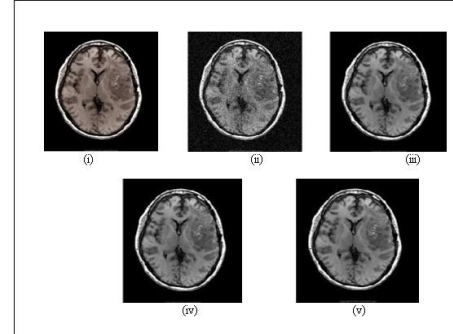


Figure 5. Results of proposed method (I) original image (II) noisy image (III) SYMLET image (IV) CNN Image (V) Neuro-SVM image for CT-Brain

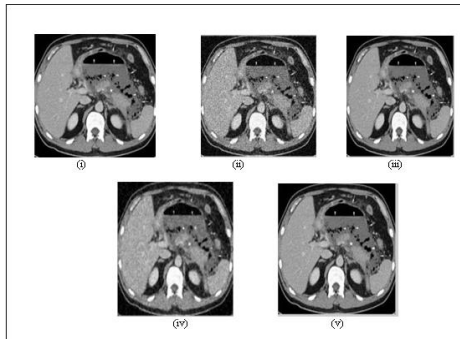


Figure 4. Results of proposed method (I) original image (II) noisy image (III) SYMLET image (IV) CNN Image (V) Neuro-SVM image for CT-Abdomen

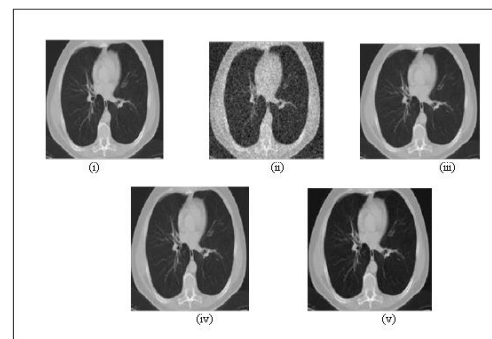


Figure 6. Results of proposed method (I) original image (II) noisy image (III) SYMLET image (IV) CNN Image (V) Neuro-SVM image for CT-Lungs

different biomedical images like X-Ray, CT, Ultrasound, PET, and MRI images. The proposed method is applied to as many as 10 different biomedical images of human body organs. The performance of the proposed method is shown on

additive Gaussian noise. The clean biomedical images are corrupted with Gaussian noise prior to applying the proposed CNN based technique. The results demonstrate that the method exhibits superiority for different kinds of images considered

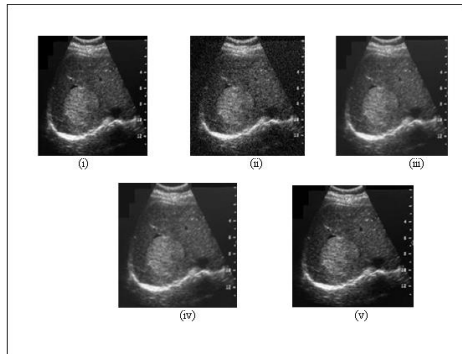


Figure 7. Results of proposed method (I) original image (II) noisy image (III) SYMLET image (IV) CNN Image (V) Neuro-SVM image for Hepatic-MRI

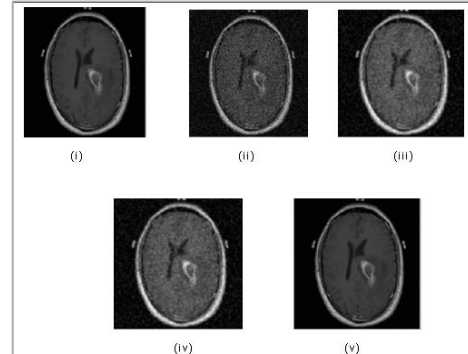


Figure 10. Results of proposed method (I) original image (II) noisy image (III) SYMLET image (IV) CNN Image (V) Neuro-SVM image for Brain MRI

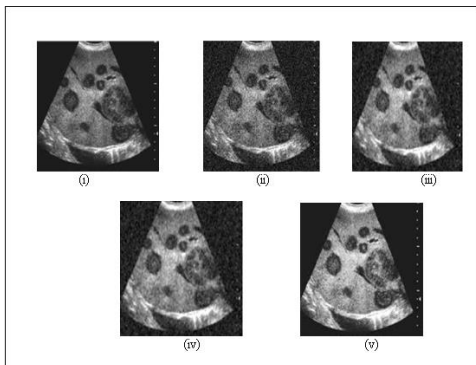


Figure 8. Results of proposed method (I) original image (II) noisy image (III) SYMLET image (IV) CNN Image (V) Neuro-SVM image for Liver ultrasound

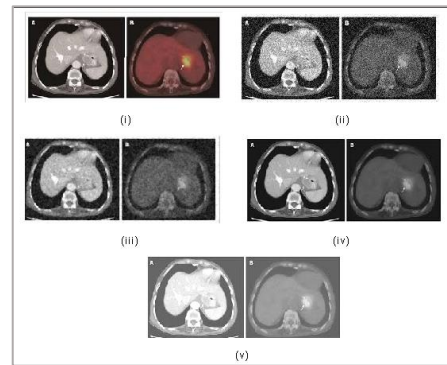


Figure 11. Results of proposed method (I) original image (II) noisy image (III) SYMLET image (IV) CNN Image (V) Neuro-SVM image for PET Gastric image

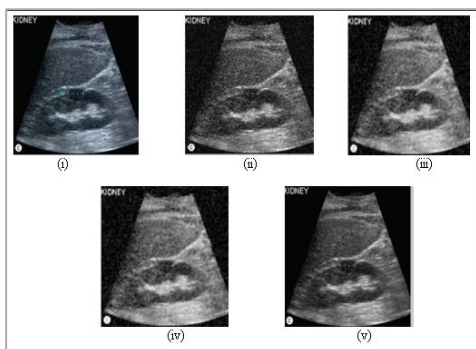


Figure 9. Results of proposed method (I) original image (II) noisy image (III) SYMLET image (IV) CNN Image (V) Neuro-SVM image for Kidney ultrasound

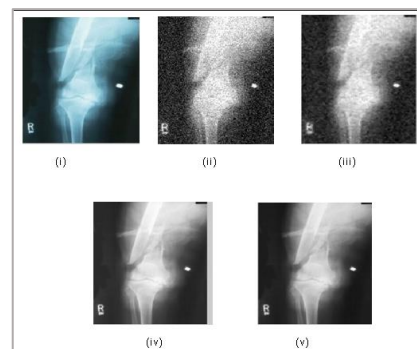


Figure 12. Results of proposed method (I) original image (II) noisy image (III) SYMLET image (IV) CNN Image (V) Neuro-SVM image for Leg X-Ray image

under study, so we can say that the proposed technique is a generalized one that works well irrespective of the type of the biomedical image used by providing better SSIM, Beta and reduced time-space complexity

Comparison of CNN based method

Compared with the neural networks, SVM, and hybrid Neural-SVM, the results of the proposed method depict better efficiency in terms of various evaluation metrics. The final results for different

biomedical images are as shown in Figures 3-12. Tables 1-10 illustrate that CNN outperforms the other soft computing techniques: neural networks, SVM, and Hybrid Neuro-SVM. The best SSIM values are obtained for the proposed method. The hybrid error values are least for the proposed technique than for Hybrid Neuro-SVM, whereas Neural networks and SVM have comparatively more values for hybrid error. The SD values are inversely proportional to the image quality. So smaller the values of SD better the image quality. From the Tables 1-10, it is apparent that for the proposed technique, the SD values are a minimum

Table 1. Brain MRI image

Method	SSIM	Hybrid Error	CNR	SD	BETA	Sensitivity	Specificity
BFO	0.6537	14.0724	0.9185	1.978	2.3496	0.5812	0.6501
PSO	0.6529	14.0368	0.3515	1.716	1.5058	0.5923	0.6642
Fuzzy Logic	0.6639	13.0720	0.5324	0.4556	1.4768	0.5646	0.6327
Genetic Algorithm	0.7417	12.0024	0.6692	1.7063	1.9132	0.5974	0.6654
Neural Networks	0.8322	8.6138	0.4278	1.6953	2.0109	0.6802	0.7509
SVM	0.8616	10.9950	0.1981	1.4165	1.6819	0.6932	0.7640
Neuro-SVM	0.9134	1.4575	0.0842	0.6283	2.0021	0.6664	0.7372
Proposed Method	0.9641	0.6428	1.2180	1.3425	2.1851	0.6907	0.7614

Table 2. CT Brain

Method	SSIM	Hybrid Error	CNR	SD	BETA	Sensitivity	Specificity
BFO	0.6592	15.0572	0.8553	0.9526	2.8117	0.5917	0.6649
PSO	0.6597	15.0452	0.8639	0.1822	2.0145	0.5009	0.6822
Fuzzy Logic	0.6556	15.0618	0.9267	0.3819	1.4812	0.5474	0.6483
Genetic Algorithm	0.7130	12.0051	1.3006	0.9456	1.3436	0.6289	0.6999
Neural Networks	0.8449	17.2080	1.3731	0.7452	2.3858	0.6977	0.7684
SVM	0.9081	10.7919	1.702	2.3882	2.4145	0.7109	0.7817
Neuro-SVM	0.9626	1.0592	0.3895	1.3451	1.7458	0.6740	0.7447
Proposed Method	0.9738	0.5081	0.7622	0.7805	2.6011	0.7282	0.7989

Table 3. CT Abdomen

Method	SSIM	Hybrid Error	CNR	SD	BETA	Sensitivity	Specificity
BFO	0.6659	16.1126	0.1521	1.5798	2.7222	0.5441	0.6217
PSO	0.6618	16.1932	0.3677	1.1188	2.1685	0.5102	0.6001
FUZZY LOGIC	0.6564	16.21753	0.8308	0.4907	2.4058	0.5464	0.6123
Genetic Algorithm	0.7043	10.0060	0.9575	1.3231	2.2712	0.5867	0.6848
Neural Networks	0.8825	8.7985	0.2486	1.335	2.1069	0.6494	0.7201
SVM	0.9429	12.7394	0.7203	2.2204	2.2505	0.6303	0.7010
Neuro-SVM	0.9602	1.8142	1.4261	0.8527	2.5622	0.6446	0.7151
Proposed Method	0.9544	1.8846	0.3456	0.7906	2.3473	0.7161	0.7869

Table 4. CT Lungs

Method	SSIM	Hybrid Error	CNR	SD	BETA	Sensitivity	Specificity
BFO	0.6545	10.0923	1.4720	1.2948	2.0162	0.5127	0.6321
PSO	0.6562	10.0815	0.4619	0.9737	2.6571	0.5043	0.6311
Fuzzy Logic	0.6610	8.0134	0.9149	0.9964	1.5289	0.5130	0.6009
Genetic algorithm	0.7041	4.0062	0.9984	1.1646	1.4227	0.5412	0.6514
Neural Networks	0.8536	2.7887	1.9305	1.6207	2.4232	0.7125	0.7832
SVM	0.8698	10.2617	0.4770	2.4299	2.0913	0.6604	0.7312
Neuro-SVM	0.9552	1.6686	1.0513	2.2834	2.6862	0.6309	0.7013
Proposed Method	0.9759	1.0061	0.7570	2.234	2.0168	0.6406	0.7016

Table 5. Hepatic MRI

Method	SSIM	Hybrid Error	CNR	SD	BETA	Sensitivity	Specificity
BFO	0.6639	7.0463	0.9778	0.9269	2.7486	0.5131	0.6180
PSO	0.6680	7.0051	0.5579	0.0195	2.2353	0.5189	0.6283
Fuzzy Logic	0.6586	8.0113	0.6796	0.3067	1.2499	0.5109	0.6134
Genetic Algorithm	0.7160	5.0049	0.9716	0.8736	2.289	0.5542	0.6519
Neural Networks	0.8462	4.927	1.129	1.534	2.0155	0.6382	0.7089
SVM	0.8531	10.987	0.9768	1.8172	2.3976	0.689	0.7598
Neuro-SVM	0.9373	1.4827	1.4913	0.9466	2.1529	0.6202	0.7273
Proposed Method	0.9280	0.4879	1.2671	0.5214	2.099	0.6554	0.7262

Table 6. Liver Ultrasound

Method	SSIM	Hybrid Error	CNR	SD	BETA	Sensitivity	Specificity
BFO	0.6523	10.2822	1.4707	1.9006	2.1063	0.5015	0.6173
PSO	0.6653	10.0748	0.5245	0.1406	1.8484	0.5107	0.6255
Fuzzy Logic	0.6578	10.3965	0.7342	0.7807	2.4799	0.5233	0.6187
Genetic Algorithm	0.7320	8.0027	1.1984	1.1109	2.6094	0.5427	0.6535
Neural Networks	0.8763	13.5000	1.5604	0.4355	2.1591	0.7155	0.7863
SVM	0.8819	10.9222	0.7793	0.2998	1.9300	0.6803	0.7501
Neuro-SVM	0.9570	1.1614	2.0952	0.7729	1.5804	0.6423	0.7130
Proposed Method	0.9984	0.9122	1.3327	0.2931	2.0760	0.6253	0.7135

Table 7. Kidney Ultrasound

Method	SSIM	Hybrid Error	CNR	SD	BETA	Sensitivity	Specificity
BFO	0.6501	8.2861	1.1367	1.2161	2.6378	0.5132	0.6192
PSO	0.6674	8.0653	0.3457	0.5464	2.1403	0.5168	0.6228
Fuzzy Logic	0.6560	8.3186	0.4432	0.6858	2.0307	0.5291	0.6119
Genetic Algorithm	0.7057	5.0019	0.9986	1.0382	2.3327	0.5479	0.6812
Neural Networks	0.8583	2.1240	1.7891	1.8266	1.4452	0.6853	0.7560
SVM	0.8508	11.9870	1.4218	1.1801	2.2091	0.6468	0.7176
Neuro-SVM	0.9751	1.3046	1.7166	1.6290	1.8609	0.6769	0.7476
Proposed Method	0.9780	0.5798	0.9847	0.7774	2.1514	0.7120	0.7827

Table 8. Brain MRI

Method	SSIM	Hybrid Error	CNR	SD	BETA	Sensitivity	Specificity
BFO	0.6699	8.4904	1.7024	0.8362	2.7023	0.5290	0.6139
PSO	0.6652	8.0459	0.8373	0.2409	1.6647	0.5217	0.6358
Fuzzy Logic	0.6500	8.0622	0.2080	1.4625	1.5609	0.5909	0.6603
Genetic Algorithm	0.7418	6.0021	1.8477	0.8075	1.9913	0.6185	0.6819
Neural Networks	0.8477	6.4847	1.6524	2.2303	1.7231	0.6829	0.7537
SVM	0.8732	12.0000	0.8628	1.1768	2.0450	0.6600	0.7307
Neuro-SVM	0.9013	1.5271	1.3931	0.7812	1.7791	0.6909	0.7616
Proposed Method	0.9088	0.3549	0.9222	0.5885	2.3432	0.7185	0.7892

Table 9. PET Gastric image

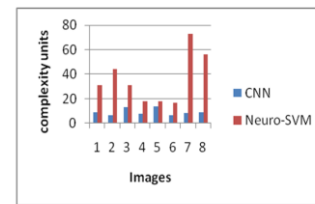
Method	SSIM	Hybrid Error	CNR	SD	BETA	Sensitivity	Specificity
BFO	0.6562	8.4490	1.7139	0.7326	2.117	0.5120	0.6313
PSO	0.6574	8.0192	0.8837	0.2340	1.6467	0.5128	0.6358
Fuzzy Logic	0.6639	8.0222	0.4208	1.4065	1.5109	0.5809	0.6618
Genetic Algorithm	0.7155	6.0121	1.8327	0.8175	1.2922	0.6285	0.6891
Neural Networks	0.7477	5.9847	1.2524	2.2012	1.7312	0.6229	0.7335
SVM	0.7732	10.0230	0.7868	1.1576	2.0045	0.6600	0.7107
Neuro-SVM	0.7813	1.5271	1.4931	0.7012	1.7091	0.6199	0.7416
Proposed Method	0.7988	1.3049	1.2222	0.7885	1.7432	0.6385	0.7592

Table 10. X-Ray Leg image

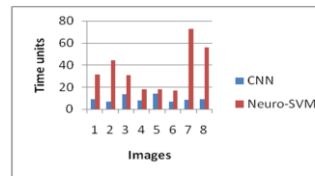
Method	SSIM	Hybrid Error	CNR	SD	BETA	Sensitivity	Specificity
BFO	0.5698	9.4004	1.7402	0.8326	2.0733	0.5120	0.6193
PSO	0.5625	9.0945	0.8337	0.2040	1.6467	0.5127	0.6318
Fuzzy Logic	0.5500	9.0622	0.2182	1.4225	1.5909	0.5909	0.6603
Genetic Algorithm	0.6481	7.0021	1.8477	0.8572	1.9913	0.6585	0.6181
Neural Networks	0.7075	7.0001	1.6424	2.2003	1.7123	0.6282	0.7357
SVM	0.6926	11.0000	0.8286	1.1076	2.0040	0.6060	0.7037
Neuro-SVM	0.7808	2.5271	1.3193	0.7181	1.7179	0.6090	0.7616
Proposed Method	0.7968	1.3495	0.9124	0.5888	2.1852	0.7018	0.7982

of all the four compared techniques. Other performance metrics such as Beta, Sensitivity, and Specificity have considerably good values for the proposed method as compared to Neuro-SVM. Although the Neuro-SVM technique and the proposed technique both have better results as compared to Neural networks and SVM, the proposed technique outperforms the Neuro-SVM technology as it has small values for computational time. The graph in Figure 13 indicates the time and space complexity comparison of the Proposed and Hybrid Neuro-SVM techniques.

As a further illustration, the confusion matrix for the proposed technique using CNN is shown in Figure 14, representing the pixel values where noise components exist. The Figure includes training confusion matrix, validation confusion matrix, test confusion matrix, and all confusion matrix for CT abdomen image.



(i)



(ii)

Figure 13. Space complexity (i) and time complexity (ii) comparison for the Hybrid Neuro-SVM and Proposed technique for different images

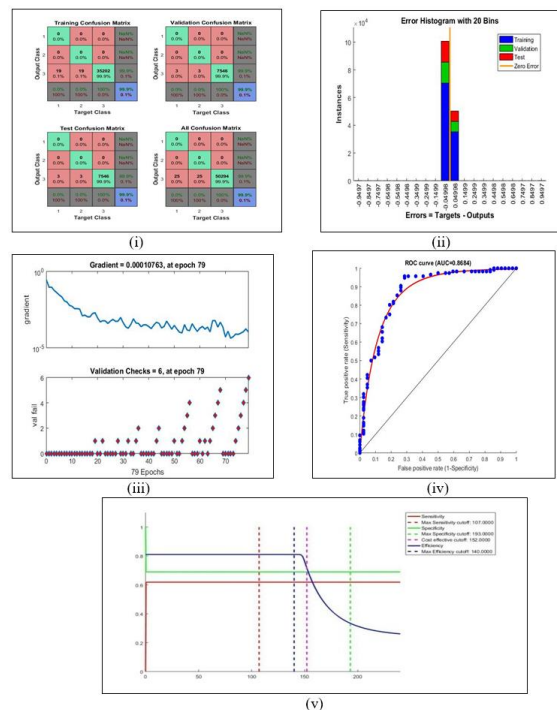


Figure 14. (I) Confusion matrix, (II) Error histogram, (III) Gradient Curve, (IV) ROC curve, (V) Sensitivity curve of proposed method for CT abdomen image respectively

image. The CNN ROC curve, Gradient curve, sensitivity curve, and error histogram are shown in Figure 14.

Discussion and Conclusion

In the proposed method, a new enhancement technique using convolution neural networks has been used. The comparison of the proposed method with neural networks has been made. The results show that the proposed method outperforms the hybrid Neuro-SVM technique, neural networks, and SVM in terms of better SSIM, Beta, Sensitivity, Specificity, and minimum time and space complexity. The new method has less error value and computation time than the hybrid Neuro-SVM technique. The higher SSIM and Beta values mean lesser value of noise in the image and better visual enhancement of biomedical images. The results for the proposed technique offered better quality images whether it was an MRI, CT, X-Ray, PET, or Ultrasound images. The only exception was for PET images where SSIM and Beta values were not better. Thus CNN based method is robust to different kinds of images.

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