

Efficient Detection of Ischemic Stroke from MRI Images Using Wavelet Transform

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Abstract: This paper deals with detection of Ischemic stroke which happens because of blockage in arteries of human brain. The obtained input MRI images are pre-processed and enhanced using filters and image processing techniques. The line of symmetry of brain is traced using an algorithm after applying watershed transform. Based on this, the image features for the brain's right and left side are calculated by means of the Gray Level Co-occurrence Matrix. Wavelet transform is applied for the enhanced image. The image features from the GLCM and the significant coefficients of wavelet transform are given as the input vector to the neural network to classify the MRI images into abnormal and normal. The lesion regions from the abnormal images are segmented using the intensity difference of the image and the lesion region. It was observed that the neural network has an efficiency of 90%. Finally; the neural network is implemented on Field Programmable Gate Array Spartan3E using system generator and Xilinx design suite14.3.

Keywords: Ischemic stroke, Gray Level Co-occurrence Matrix (GLCM), Artificial Neural network (ANN), Field Programmable Gate Array (FPGA).

I. INTRODUCTION

According to statistics from World Health Organisation (WHO) 15million people are affected by Cerebrovascular accident or Stroke worldwide. Among those 5 million die and 5 million are damaged permanently. Stroke happens because of disturbance in blood flow in the arteries leading to and within brain which results in loss of brain function. If part of brain dies due to lack of blood supply, part of body which is controlled by that is affected. Strokes can result in paralysis, emotional problems, affect vision and language and lead to other problems in body. The disturbance can be due to haemorrhage or ischemic. Haemorrhage is rupture of brain artery and Ischemic is occlusion of an artery. Ischemic stroke represents about 87% of all strokes. Recovery from stroke is long term. Hence, there is a need for techniques and tools to predict Stroke. MRI or CT images of brain are necessary for the diagnosis of stroke. MRI images are more suited for spinal cord injury, brain tumours, ligaments and tendon injury and for soft tissues like eyes, brain and heart. Advantages of MRI over CT scans are that they don't use ionizing radiations and greater range of contrast is available for soft tissues. MRI images also give information about the flow of blood in blood vessels and few organs. Hence, these images can be used for detection of problems associated with blood circulation and blockages.

Soft computation techniques such as genetic algorithms, fuzzy logic, rough sets and neural network will lead to an intelligent, low cost and interpretable solution than traditional techniques. Artificial neural networks offer an efficient tool to aid doctors analyse, model and help to predict the disease based on the data hidden in the database. Neural network implementation in FPGA (Field Programmable Gate Array) offers flexibility in programmable systems. FPGAs have smaller size and higher speed for real time application.

Vast amount of study has been done on early detection of stroke. Based on research done by A. Przelaskowski^[1] hypodense areas were detected from non-enhanced CT images using Wavelet Image processing for perception enhancement. Additional clinical tests are required to enhance display methods. In the paper by Tomasz Hachaj^[2] existing image processing schemes were modified to increase the efficiency to detect and classify perfusion irregularities by

addition of multilayer perceptron neural network. Self-organizing Kohonen's map (SOM) architecture was used for image processing. In the work done by Branko N. Huisa^[3], diffusion-weighted imaging with Computed tomography perfusion (CTP) mapping was used to differentiate ischemic penumbra from infarct core. It was observed that acute stroke imaging, CTP offered a lesser amount of sensitive for predicting acute Ischemic Stroke. In research done by N. HemaRajini^[4] Computer aided detection was done using segmentation, image feature characteristics and mid-line shift from CT images. These image features were given as input vector to ANN, k-NN, SVM and decision tree classification. In the paper by Fuk-hay^[5] Tang computer aided detection scheme was used to detect Ischemic stroke. Circular Adaptive Region of Interest (CAROI) technique is proposed to analyse the CT brain images. Texture analysis was done to study the image features that detect the stroke lesions.

In this paper, the acquired MRI^[6] images were pre-processed using Median filter and enhancement was done using imadjust. Watershed transform was used to trace the midline symmetry of brain. Gray Level Co-occurrence matrix was found for brain's left and right after splitting it according to midline symmetry. Image features such as correlation, contrast, homogeneity and energy were calculated from the GLCM^[7]. Wavelet transform^[8] was applied for the images and the coefficients were calculated. The image features from GLCM and wavelet transform were given as the input vector to train the neural network. Based on the output from the neural network the images were classified as normal and abnormal images. For the abnormal images segmentation based on the intensity was performed to detect the lesion region. Artificial neural network was implemented on FPGA^[9] using system generator and Xilinx ISE 14.3.

II. PROPOSED METHOD

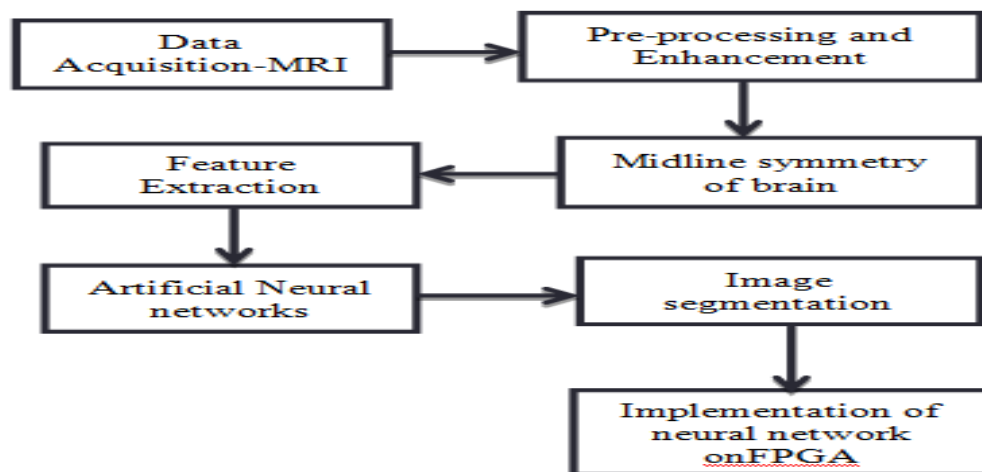
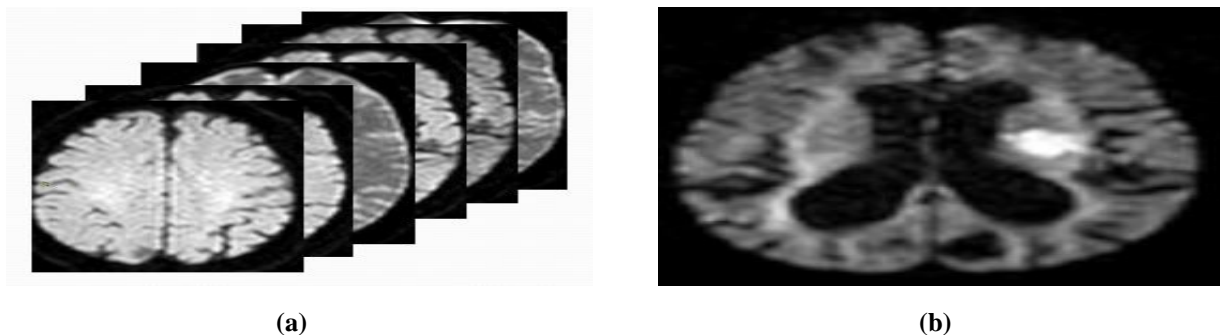


Fig. 1: Block diagram of proposed model

A. Data Acquisition

Set of MRI images were collected from a hospital. Ground truth was done by consulting a neuro surgeon. 2 set of data were collected from different patients who were diagnosed with stroke. Each set consists of 30 slides of images. Each set had few images with lesion region.



(a)

(b)

Fig. 2: (a) Set of MRI images (b) Image with Lesion region

B. Pre-processing and Enhancement

Median filter using 3-by-3 square was applied to reduce noise. Median filter is chosen because it helps to remove the outliers without decreasing the sharpness of the image and is less delicate to extreme values. After applying median filter abnormalities become more conspicuous in the homogenous background which is produced.

There is a need to perform intensification between the lesion region and brain. The contrast between the lesion region and normal brain is below the human perception. Thus, Imadjust is used for image enhancement. Imadjust maps the intensity of a gray scale image to a new value which is 1% of data saturated at high and low intensities. This enhances the contrast of the image.

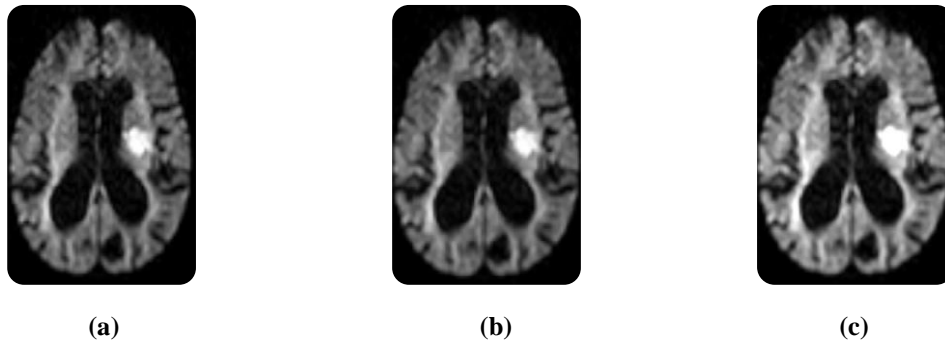


Fig. 3: (a) MRI image, (b) image after Median filter (c) Image after enhancement

C. Marking out midline of brain

Human brain is approximately bilaterally symmetrical. Classification of human brain into abnormal or normal depends on the structures on right and left hand side of the brain. Therefore it is necessary to develop an algorithm that traces the midline of the brain for the accurate classification. The proposed algorithm is efficient even for asymmetrical brain. Initially segmentation of brain using watershed segmentation which helps to get the brain image separated from the background. The obtained image after segmentation is with the complete brain in white color and the background in black color. Now middle pixel of each white part is found out using a proper logic. All the mid points are joined to trace the midline of the brain.

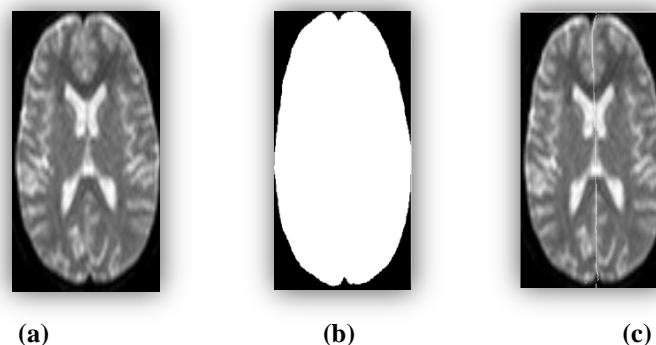


Fig. 4: (a) input image (b) After segmentation (c) Midline traced for the image

D. Feature Extraction

i. Texture Analysis

The texture of the image is the local variations in the image intensity. Texture analysis can be statistically done using co-occurrence matrix. This matrix is generated from the estimation of pair wise statistics of the image pixel intensity. Gray Level Co-occurrence Matrix (GLCM) is constructed on the theories that in a texture identical grey level configuration is recurrent. The co-occurrence matrix is given as $P(i, j | d, \Theta)$ where i and j are grey level values at a distance d with an angle Θ . With GLCM second order statistical features can be extracted. Number of columns and rows are equal in the GLCM. The following notations are used in GLCM.

μ – Mean value of P

μ_x and μ_y -Mean value of P_x and P_y

σ_x and σ_y - Standard deviation of P_x and P_y

G – Size of co-occurrence matrix

The subsequent GLCM features were used in this work.

Energy, Correlation, Contrast and Homogeneity

Energy: It gives the uniformity of the Image. For a constant image energy is 1.

$$Energy = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j)^2$$

Correlation: gives the measure of level dependency amid the pixels at the relative position to each other which is specified. For a considerable linear structure image the correlation will be high.

$$Correlation = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{i, j\} \times P(i, j) - (\mu_x \times \mu_y)}{\sigma_x \times \sigma_y}$$

Contrast: It is the amount of local differences of an image. This gives the degree of contrast favours influences from $p(i, j)$ from the diagonal element $i=j$. Larger the variations in the image ,from the diagonal $P(i, j)$ s will be concatenated and results in higher contrast.

$$contrast = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j) \right\}, |i - j| = n$$

Homogeneity: It gives the measure of nearness of the components in GLCM with the diagonal of the GLCM matrix. For the diagonal elements homogeneity is 1. Co-occurrence matrix of homogenous image is a mixture of high and low $P[i, j]$'s whereas heterogeneous images gives an equal spread of $P[i, j]$'s.

$$Homogeneity = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{P(i, j)}{1 + |i - j|}$$

These GLCM features were calculated for both the sides of the brain that was obtained after tracing the midline of the brain. The ratio of left by right was calculated and was given as the input vector to the neural network along with the wavelet transform coefficients.

ii. Wavelet Analysis

An image can be approximated by a matrix A which has the corresponding gray level pixel intensities $P(i, j)$ [10] as the elements of the matrix. A is a square of dimension $2^n \times 2^n$, where n is a integer. The procedure of wavelet transform is as follows: filters G and H are applied for the rows of the A matrix. The resulting matrices are $H_r A$ and $L_r A$ of size $2^n \times 2^{n-1}$. Now the column matrix of $H_r A$ and $L_r A$ are again applied with G and H filters which results in four matrices $H_c L_r A$, $H_c H_r A$, $L_c L_r A$, $L_c H_r A$ of size $2^{n-1} \times 2^{n-1}$. The matrix $L_c L_r A$ is the average matrix and others are detail matrix. Similarly many level of decomposition can be performed.

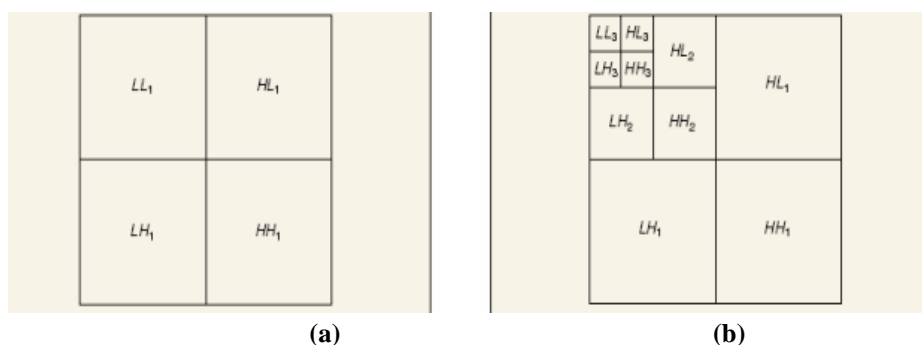


Fig. 5: (a)decomposition at level 1 (b) decomposition at level3

E. Artificial Neural Networks

Artificial Neural Networks (ANNs) can resolve of difficulties in areas of pattern recognition, image processing and medical diagnostic. Back propagation is the algorithm which incorporates supervised learning, which is used with multi layered feed forward network. The neurons are arranged in layers, the signal is sent forward and the error is propagated backward. The input to the network is given through the input layer and from the output layer the output is obtained. A network can have one or more hidden layers. Back propagation aims at reducing the error until the network learns the training data. The input gets multiplied with the weight and this is sent to a activation function and the output of the activation function is given to the next layer.

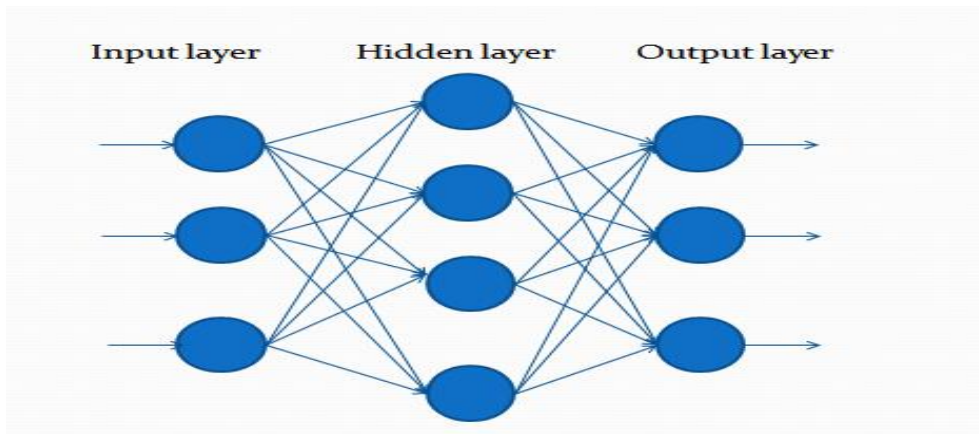


Fig. 6: Artificial neural network

F. Image segmentation

Based on the results from the neural network the abnormal slides of images are separated from the set of input images. For the abnormal set of images the feature extraction technique is applied to detect the lesion region. The lesion region was cropped from the image and histogram was plotted for that region to find the range of intensity of the lesion region. This was done for all the images and an approximate range of intensity was noted down. Based on the intensity the lesion region was separated. If the region other than the lesion was detected then it would be found on both sides of the brain. By exploiting the symmetry of the brain the left part of the brain was subtracted from the right side. This resulted in the detection of the lesion region alone.

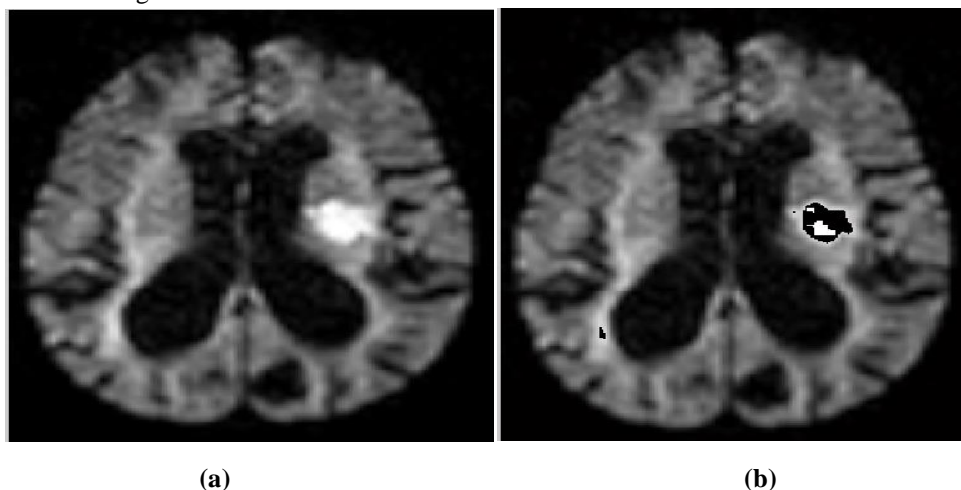


Fig. 7: (a) Input image (b) lesion detected image

G. Implementation Of Neural Network On FPGA

The neural network was implemented on Xilinx Spartan 3E FPGA. The features of the XLINIX Spartan 3E are as follows: It is Very low cost and used for consumer-oriented applications. It consists of 216k block RAM bits, 250k no of gates, 38K distributed RAM, dedicated multipliers 12,5508 equivalent logic cells, bits, 2448 Configurable Logic Blocks.

The code for the FPGA was generated by the system generator tool box in MATLAB. The model for the neural network was built using the Xilinx Simulink blocks and this model was converted to Verilog code. This code was dumped on the hardware to design the neural network in FPGA.

III. RESULTS

The table below shows the image features from the GLCM and the approximation coefficients of the wavelet transform. It was observed that approximations of wavelet transform gave much significant change from normal to abnormal. Hence, only approximations were considered as input vector than the detail coefficients. Table 2 shows the values of image features and wavelet coefficients. 2 sets of images each containing 30 images were tested for same features and based on that the input vector and the target vector were decided.

Table 1: Normal Images Data

Normal Image				
	Image features	Left (L)	Right (R)	L-R
GLCM	Energy	0.202	0.1832	0.0188
	Correlation	0.9774	0.9813	-0.0039
	Contrast	0.1238	0.1237	0.0004
	Homogeneity	0.9432	0.9389	0.0043
Wavelet coefficients	Approximations	Level 1	Level 2	
		205.6267	409.4252	

Table 2: Abnormal Images Data

Abnormal Image				
	Image features	Left (L)	Right (R)	L-R
GLCM	Energy	0.1537	0.1553	-0.0016
	Correlation	0.9707	0.9795	-0.0088
	Contrast	0.2052	0.1499	-.0053
	Homogeneity	0.9234	0.9251	-0.0017
Wavelet coefficients	Approximations	Level 1	Level 2	
		188.8847	375.1372	

The neural network is designed for 6 input vectors for the input layer and 1 output from the output layer. One hidden layer was used with 7 neurons in it. Neural network tool was used to design the network and to train it.

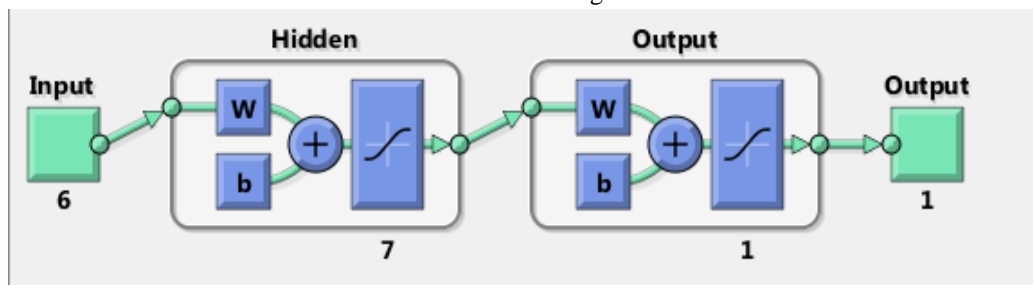


Fig. 8: Neural Network Generated By The Neural Network Tool Box

To implement the neural network on FPGA the blocks were created using Xilinx Simulink blocks. The conversion of the Simulink blocks to Verilog code was done using system generator. The network designed in hardware consists of 6 input vectors with 12 input weights. The weights calculated from the software simulation are given as the input weights. The inputs and weights are of 16 bit length.

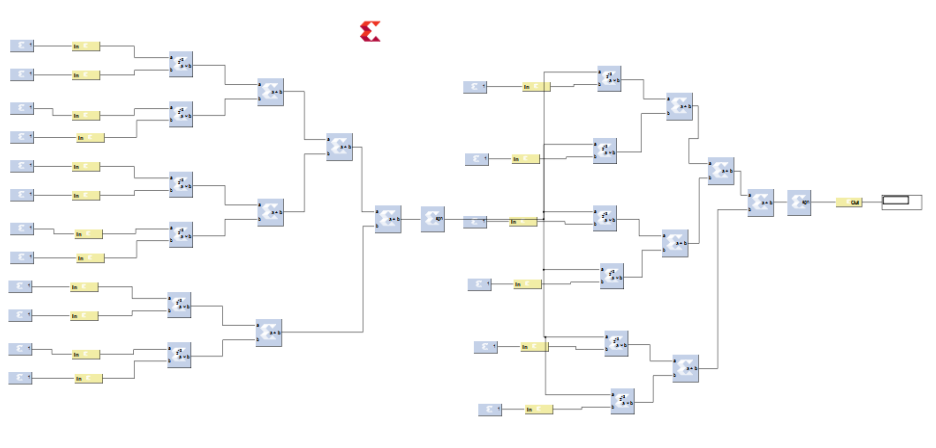


Fig. 9: Blocks generated using system generator

The generated code was synthesised and simulated using Xilinx IDE design suite and Modelsim .

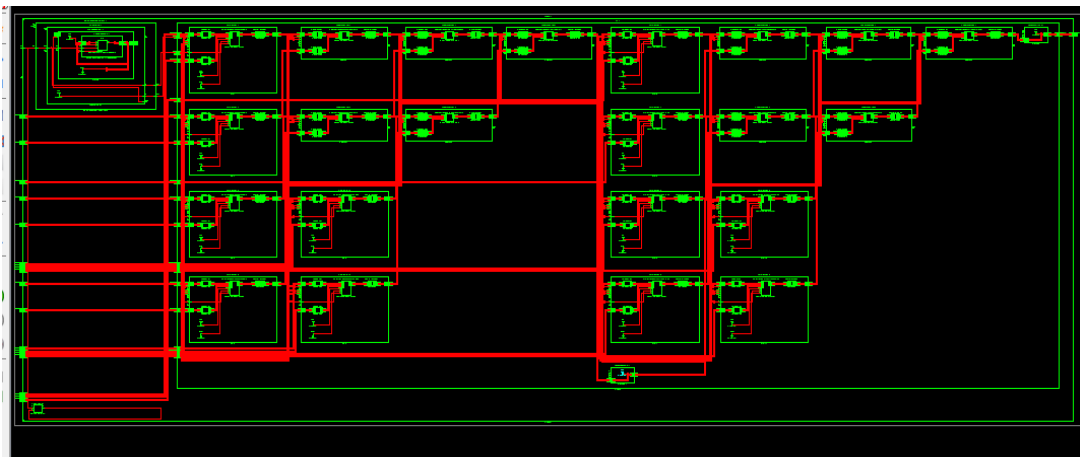


Fig. 10: RTL schematic

Different values were given as input and weights and the corresponding results after the transfer function was obtained. The wave shows the input ,weights and the corresponding output.

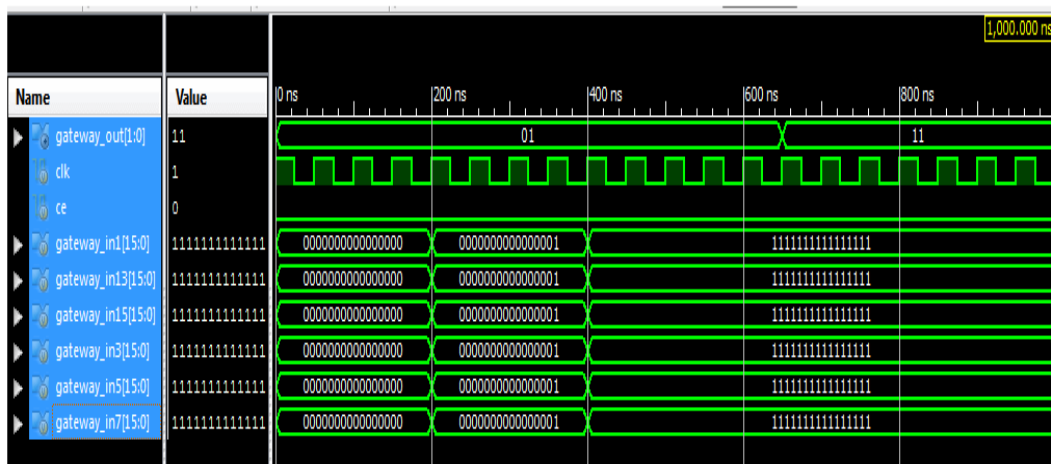


Fig. 11: Simulation results

Due to unavailability of input switches and only integers can be given as input switched, only a part of the design was implemented on the hardware. In this design 2 inputs were multiplied with their corresponding weights and the product of these was added and was displayed as the output through the LEDs on the board.

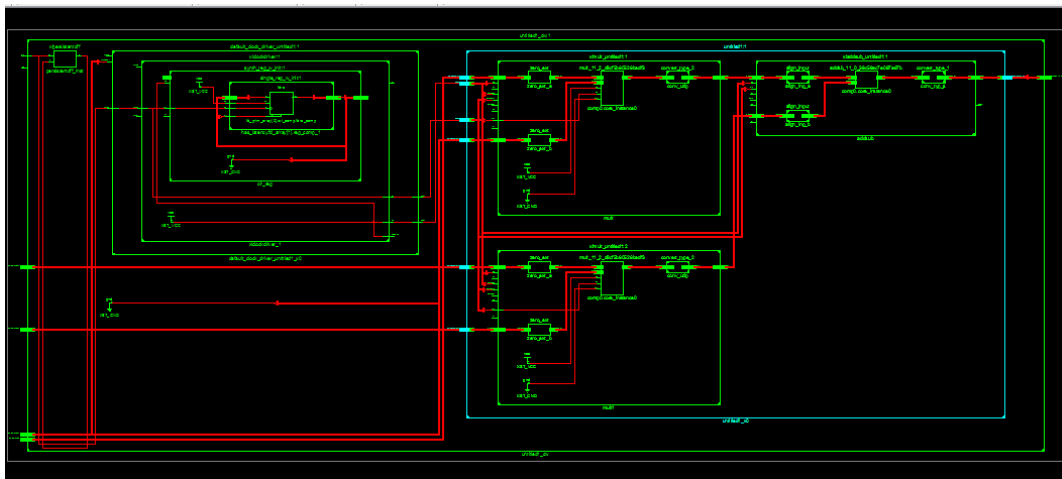


Fig. 12: RTL schematic

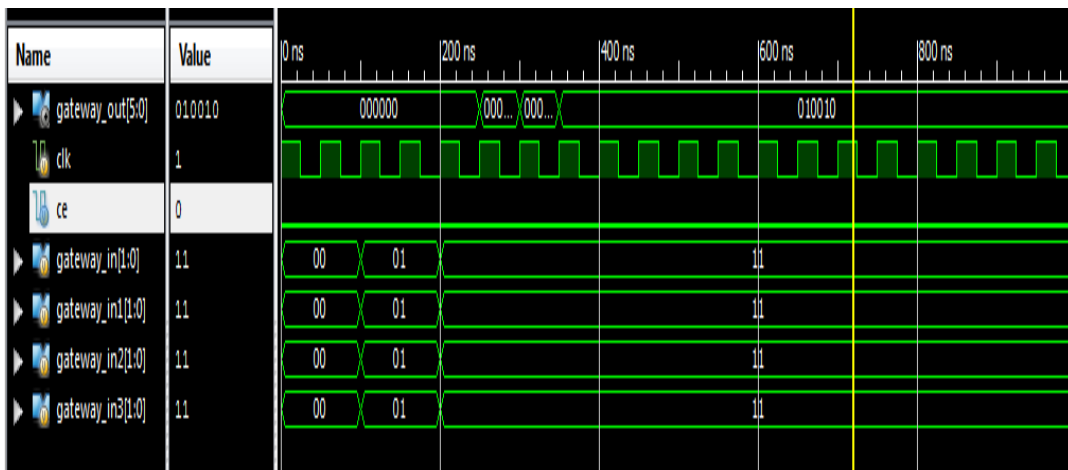


Fig. 13: Simulation output

If inputs and weights are 3 then the output is 18 which are 10010 in binary.



Fig. 14: Hardware implementation

IV. CONCLUSION

This work presents an efficient approach for identifying and detecting the lesions from the input MRI images. Combining the statistical texture features with wavelet based features has significantly increased the accuracy of the proposed work. Also, the hardware implementation of the presented approach for detecting the lesion is also presented.

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