GENERALIZED FUNCTIONAL ADDITIVE MODEL FOR VALIDATING THE SPIKE TRANSFORMATION OF FNDCNN USING 2D IMAGES

Dr.P.Nancy
Assistant Professor
Department of CSE

T.M.Angelin Ben Roja
Department of CSE
JP College of Engineering

JP College of Engineering

Dr.E.A.Mohamed Ali
Assistant Professor
Department of CSE
JP College of Engineering

ABSTRACT

Understanding, enhancing, healing, and repairing the neural system is a predominant and fast-growing research area of neural engineering and neuroscience. The Convolution Neural Network (CNN/ConvNet) is a popular and preferred choice of researchers to identify the neural functions because of its attractive features in image recognition. Moreover, the linear nature of CNN reduces its effectiveness to identify the neural activity based on image classification. Hence, a novel Fuzzy Logic Non-linear Deep Convolution Neural Network (FNDCNN) is proposed in this paper to overcome the limitation of conventional CNN. The proposed novel deep learning FNDCNN approach is used to model neural spiking activity of the brain cells that is able to predict the output neural spiking activity from the input. The nonlinear activation dynamic of the FNDCNN is introduced by fuzzy logic function in higher-order kernels. The performance of the proposed novel deep learning approach designed for Multi-input Multi-output (MIMO) system is tested and compared with the recent techniques such as conventional CNN, MicroNet, and GLM in terms of correlation coefficients and Normalized Root Mean Square Error (NRMSE) between actual and predicted output neural spiking activity. The proposed FNDCNN algorithm improves the accuracy and performance of the MIMO system model and also ensures better results when compared with the conventional CNN, Micronet, and GFM.

Keywords: ***Non Linear CNN, Neural spiking, Fuzzy, Generalized functional additive model.***
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I. INTRODUCTION

Convolution Neural Network (CNN) is used as a benchmark model and also a base architecture by researchers for image recognition since 2012 after winning the first image recognition contest held in

2011[17,25]. In addition to the image recognition tasks, it also exhibits superior performance in time series analysis, natural language processing, and speech recognition. It works like a visual cortex and also recognizes images from the input image that enters into the feature extraction process then, the extracted feature signal is fed to the classification process of the neural network. Consequently, the classification process in this deep learning operates based on the features of the image that is being selected and generates the output. The feature extraction layer of Convolutional Neural Network (CNN) consists of convolution layer and pooling layers pairs. As its name implies, the convolution layer performs as a collection of digital filters and converts the image using the convolution operation. Next, the pooling layer combines the neighboring pixels into a single pixel therefore the pooling layer reduces the overall dimension of images to the required size for the operation. Hence, the pooling is also called down sampling because it reduces the dimension of an image without losing any important information regarding the image i.e., all details of the image are retained as it is since the primary concern of the CNN is the image. The operation of the convolution and pooling layers are conceptually occurring in 2-dimensional (2D) planes. After the feature extraction, it enters into the classifier layer which includes the flatten layer, and the fully connected layer. These flatten layer converts the matrix output from the pooling layer into the vector and the fully connected layer consists of a dropout layer and output layer. It is shown in Figure.1.

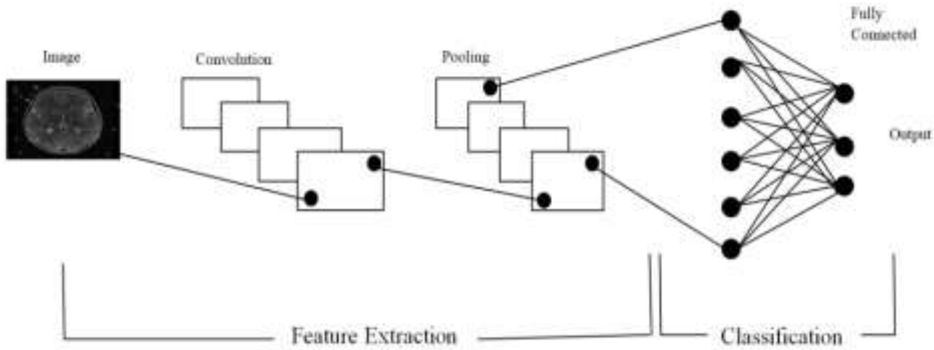

Figure.1 CNN Architecture

The CNN is the boon to the image classification. The main challenges in implementing CNN are over fitting, accuracy, NRMSE.

In Neuroscience, neural system sends information to entire human body using electrochemical reactions to coordinate all the necessary functions of life [7,8,11,12,14]. When the message going to transfer from one neuron to another, there is a rapid rise of potential in the neuron membrane that will leads to the conversion of threshold to attain activation potential. This conversion is known as spiking neural activity and the neuron with this spiking activity is called spiking neuron. During spiking brain activity, a neuron's present status is characterized as its layer potential perhaps displayed as a differential condition [30,31,32,33,34]. An info beat i.e., information passing makes the layer likely ascent for a while and afterward step by step decline. This spiking of neuron ultimately results in the conduction of messages from successive neuron. This spiking activity is happened in each and every individual neuron to form the neural spike train. However recent research proves that the existence of nonlinear operation in the response of complex brain cells coordinated to execute multiple tasks at the same time [1,2,5]. The current system implements the CNN to model output neural spiking activity from input neural spiking activity. It is able to achieve high correlation between the predicted probability of spiking in the output neuron and the true probability of spiking in the output neuron for the generated data with a generalized linear model [4,6,13].

CNN is able to recover the true model variables (kernels) used to generate the probability of spiking in the output neuron. Based on the CNN model's validation via a generalized linear model (GLM). The current system extends only up to the linear system. The GLM is the linear regression model, that allows the system to build linear relationships between predicted and actual values, even when the values are not in linear distribution [3,4].

This GLM is not suitable in two scenarios,

1. For the occurrence of Homeoscedasticity (y is not constant which varies according to x, it is also known as Variance of error in y)

2. For constructing the linear regression model for the discrete or binary data, the GLM will predict the negative value for the corresponding data [9].

The CNN is used for implementing the linear dynamics using Linear activation function like Identity function [9]. This causes problems like No possibility of back propagation, the result obtained is a constant which cannot related to the input, inflexibility, ambiguous for the real time systems. The usage of CNN is also limited to linear model because of its working implementation. In order to overcome these problem lots of non linear activations such as exponential weight, Relu, sigmoid, clipped relu etc., are being used within the CNN to convert LCNN (Linear CNN) to NLCNN (Non Linear CNN) [10,38].

Fuzzy System plays a major role in preprocessing & post processing, regulation, and error rectification. The Fuzzy Inference System (FIS) is the manner of formulating the mapping function from the given input to output using Fuzzy Set Theory. The mapping gives the foundation for which choice to make. The output from the FIS is a fuzzy set regardless of its input which can be fuzzy or crisp [15,18,19]. In this research work, the novel deep learning approach using Fuzzy logic Nonlinear Deep Convolution Neural Networks (FNDCNN) is proposed to model output neural spiking activity from the input neural spiking activity to achieve high accuracy using Generalized Functional Additive Model (GFAM). FNDCNN is the deep neural network with more than one output. This allows the system to increase the accuracy. Thus, little effort has been devoted to extent the convolution techniques to nonlinear system doing the multiple tasks.

The following section of the paper is organized as the design and implementation of FNDCNN is explained in section II, the result & discussion of the proposed method along with already reported methods is presented in section III, followed by the conclusion of the proposed method in section IV.

III. PROPOSED SYSTEM DESIGN AND IMPLEMENTATION

The proposed MIMO FNDCNN model includes a combination of a number of Muti-Input Single-Output (MISO) Deep Convolution Neural Network (DCNN) in order to capture linear dynamics using kernels and Fuzzy Logic (FL) based classifier to achieve better image recognition by incorporating nonlinear function.

A. DCNN Architecture:

The architecture of a typical MISO DCNN consists of four layers such as (i) Convolution layer (ii) Activation layer (iii) Pooling layer (iv) Fully connected layer.

(i) Convolution Layer

DCNN uses a special mathematical technique called convolution instead of matrix multiplication to extract the important features of the input image [16,21]. The convolution process is done by three inter-related operations such as convolution, kernel or filter, and dot product. The convolution layer of DCNN takes a set of weights, forms a 2D array i.e., kernel or filter, and multiplies them with the captured input image, and then the operation is repeated several times until extracting the important features from the input image.

The proposed system model uses five 2D convolutional layers (conv2D) with kernel sizes of 3x1, 3x1, 5x1, 5x1, and 7x1 respectively. Each convolution layer has sixteen filters that capture the important features and sends the feature map to the next convolution layer for further process of capturing more important features from the output pixels. The first conv2D layer normally captures the basic features like diagonal or horizontal edges. Then, the output of the first conv2D is sent to the second conv2D layer to extract complex features such as combinational or corner edges. As the extracted feature map moves deeper into the higher conv2D layer that can detect even more complex features such as faces, objects, etc. Figure 3 shows the Convolution Filter with stride (1,1) that denotes the shifting of the filter by one pixel in unit time.

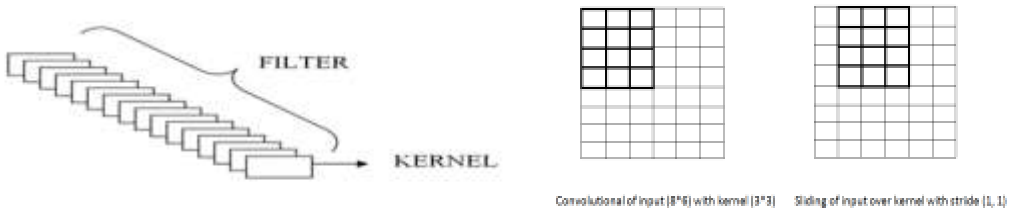

Figure 3. Convolution Filter with stride (1,1)

(ii) Activation Layer

The extracted features from the convolution filter pass through a nonlinear activation layer like Rectified Linear Unit (ReLU) to replace the negative numbers with zero. ReLU is widely used as an activation function since it works better than other nonlinear functions such as sigmoid or tanh.

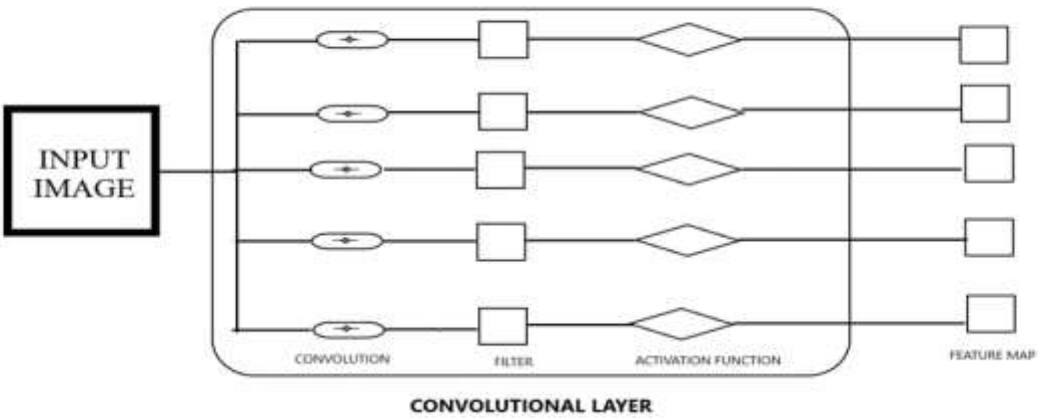

Figure4. Feature extraction from DCNN

(iii) Pooling Layer

The pooling layer of DCNN keeps the most important features of the filtered image by reducing the dimension of the input image. It can be achieved by retaining a maximum value or average value of a group of pixels. Moreover, maximum pooling is a preferable choice for its better performance. It is shown in Figure 5. The pooling layer reduces the computation complexity and number of parameters and also helps to control the overfitting.

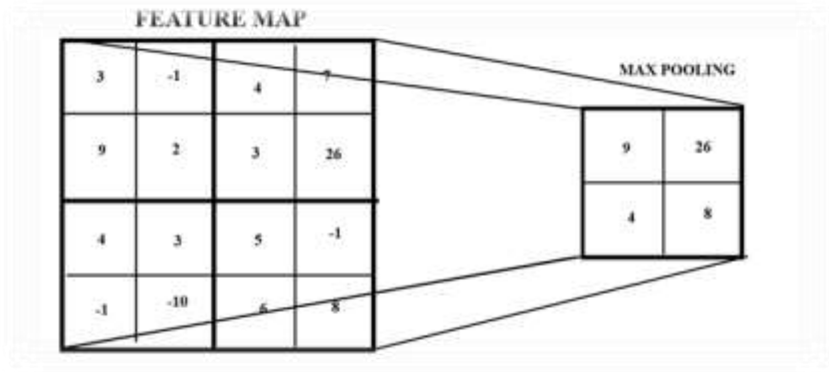

Figure 5. Max pooling operation

(iv) Fully Connected Layer

The fully connected layer receives the flattened input vector after several iterations done by the convolution layer, activation layer, and pooling layer. Finally, it uses the softmax function to classify the received flattened pixel belong to.

(B) Implementation of the FNDCNN System

A collection of the number of MISO (Multiple Input Single Output) DCNN is used to form the proposed MIMO FNDCNN model. Figure 6 shows the implementation of MIMO (Multiple Input Multiple Output) model using single MIMO DCNN. Hence, the fully connected classification layer of MIMO FNDCNN gives a set of probability values that specify how much the image is to belong to a "class." The Fuzzy Logic (FL) nonlinear activation function of the proposed system improves the accuracy of the predicted output.

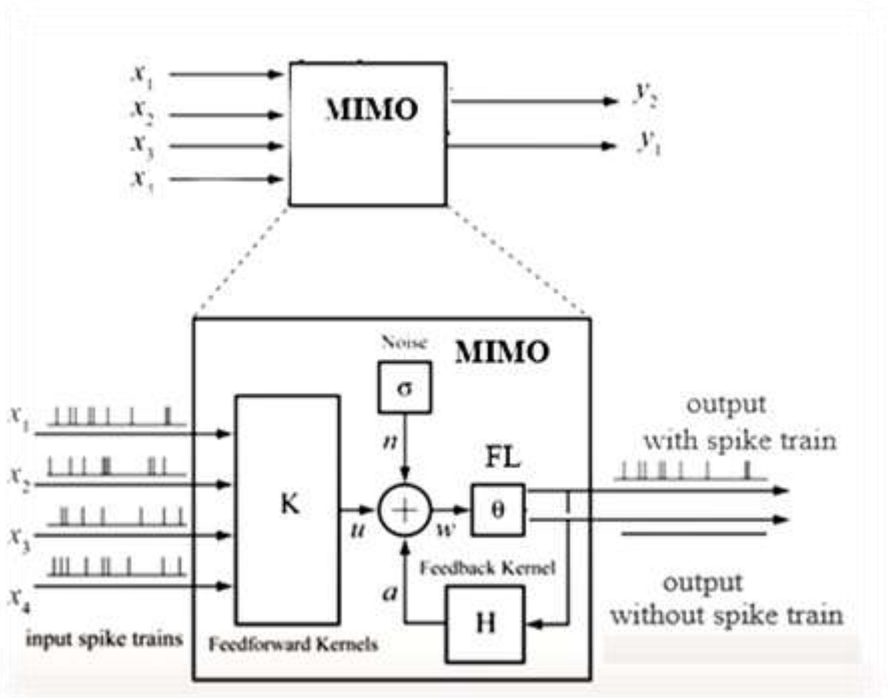

Figure 6. MIMO model using FL

The proposed novel deep learning approach using FNDCNN is used to model output neural spiking activity from the input neural spiking activity to achieve high accuracy using Generalized Functional Additive Model (GFAM). It consists of three sections namely Inputs, FL with kernel function and Output, is shown in Figure 7. The overall system architecture of the proposed system is shown in Figure 8.

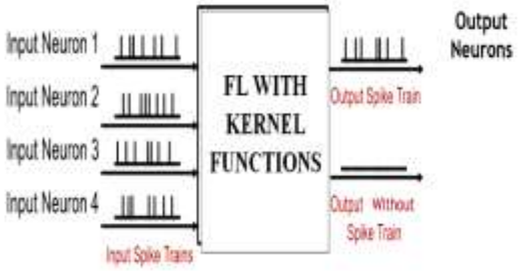

Figure7.Block Diagram of FNDCNN

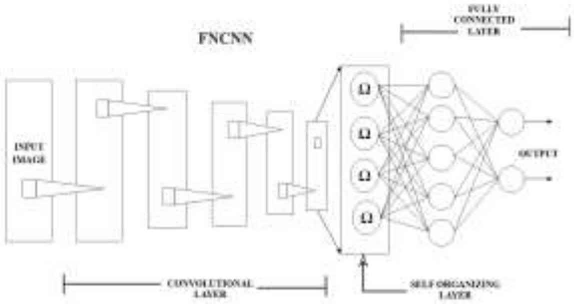

Figure 8.System Architecture

(i) Input:

FNDCNN system has two types of inputs such as neural nodes/input layer and input image dataset. Out of sixteen neural nodes, eight were connected with kernel functions, and the remaining eight kernel functions were set as zero. Here, the input neuron is defined by the spiking activity which was generated by setting the values of the zeroth-order kernel as -7.65 which can trigger (firing) at the rate of 1Hz in the output neuron (Bryan J Moore et.al). Initially, the input MRI image dataset was uniformly resized to 225 X 225 pixels in preprocessing. Consequently, the Median filtering and Gaussian filtering are applied to remove salt and pepper noise and enhance the quality of the input image respectively. Figure 9 shows the filtered image after preprocessing.

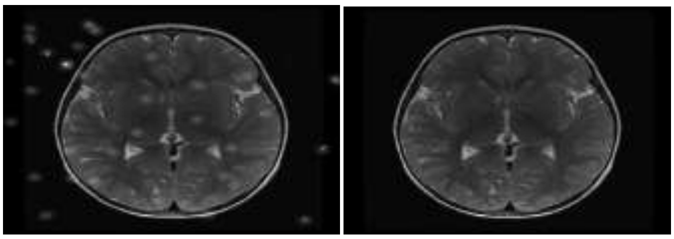

Figure 9.Noisy image and Image after Denoising

The GFAM that used to generate the ground Kernel in the output neuron.

$$E(Y/X) = h^{-1} [\, \emptyset_0 + \int g_1\{ t, x(t)\, dt \} + \; .... \; + \int g_n \{ t, x_n(t)\, dt\}]$$

TT

$\emptyset_o$= represent the average firing rate (base line firing rate) .

h = Probit link function map (0,1) to (-∞,∞).

The GFAM generates synthetic data for response. The baseline firing rate in the output neuron with each input neuron can individually convolve with one of the neurophysiological inspired kernels functions. It is shown in Figure 10.

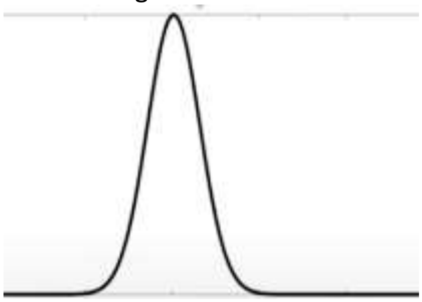

Figure10. Kernel Function

Figure 10 shows the shape of the kernel function [E(Y/X)] and then passes that sum to the inverse probate link function in order to map this range from zero to one which is the representative of the probability of spiking in the output neuron. Thus the 16 input rounds eight were generated. These neurophysiologic kernel functions and eight were generated with the kernel function 5 set to be zeros and the zeroth-order kernel represented by Øo which is set as -7.65 around 1 HZ baseline firing rate in the output neuron (Bryan J Moore et.al). This result is a high level of spiking activity in the output neuron.

(ii) FL with Kernel Function

In the proposed FNDCNN system, the fuzzy layer is primarily based on a fuzzy machine that is trained by a learning algorithm derived from Neural Networks (NN) [20,22,23]. The learning technique operates on neighborhood data (local information) and which results in local modifications within the underlying fuzzy system. A Fuzzy layer consists of a 3-layer feed-forward NN. The first layer represents enter (input) variables, the middle (hidden) layer represents fuzzy regulations and the third layer represents existing (output) variables. However, it can be handy, as it represents the data flow of entering processing and learning within the model.

A fuzzy layer can be constantly (i.e., earlier than, all through, and after learning) interpreted as a system of fuzzy set rules. It is also possible to create the system out of education records (training data) from scratch, as it is feasible to initialize it by way of past experience based on fuzzy rules. Gaining knowledge of the system of a fuzzy layer takes the semantical properties of the underlying fuzzy system into account. This outcome in constraints at the viable changes (possible modification) applicable to the system parameters.

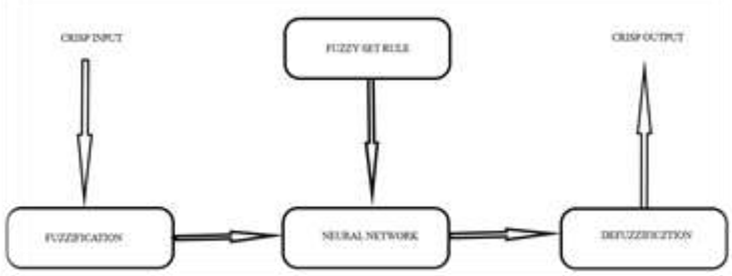

Figure 11.FIS of FNDCNN

Figure 11 shows that there are 3 type of process involved in the FIS (Fuzzy Inference System). The process involved in the fuzzy layer is mainly fuzzification - which involves in converting of crisp vale into fuzzified value, defining rule – by using fuzzy set theory the mapping function is declared for the membership function, defuzzification – involves in conversion of fuzzied value to crisp value.

The matrix X*Y is taken as the input of the self organizing layer (fuzzy system). The FIS uses the fuzzy logic edge detection algorithm for calculating the gradiatent along x and y axes for the feature map.

Fuzzy Set Rule:

The Madami theory is used to define the fuzzy set rule. IF – THEN rules are designed to comprise the knowledge base for constructing the FIS system. I_{ij} is each unique value of the pixel value here i is the value of row and j is the value of column. Thus the fuzzy rule is obtained as

Rule: if I_{ij} = = 1 and I_{ij}>> 1 then return the same value;

if I_{ij} = = 0 and I_{ij}<< 0 then return the Zero;

Defuzzification:

The matrix F(X*Y) is the output of the FIS system. Each row and column of output is defuzzified. This matrix is given as the input to the classifier.

IV. RESULT AND DISCUSSION

The proposed FNDCNN system has been implemented using keras, MATLAB R2021a and Tensor flows as the frontend, main, and backend of the DCNN architecture respectively. In this proposed research work, the Kaggle Dataset of MRI brain images is used to test the neural spiking activity of the brain. The input is converted into the digital format GFAM is used to generate the synthetic data such as predicators using the MATLABR2021a in order to test the performance of FNDCNN to recover the probability of spiking in a single output neuron over time based on the input from 16 input neurons. Thus use the recovery of the true Kernel Model that is used to generate data process as the performance matrix of FNDCNN mode.

Table 1 System Configuration

TYPE OF LAYER	FILTERS	SIZE OF FILTERS	CONVOLUTIONAL STRIDE	OUTPUT	NO. OF PARAMETERS
Conv2D	16	3,1	1,1	254,16,16	64
Conv2D	16	3,1	2,1	126,16,16	784
Conv2D	16	5,1	1,1	122,16,16	1296
Conv2D	16	5,1	3,1	40,16,16	1296
Conv2D	16	7,1	1,1	34,16,16	1808
SELF ORGANIZING LAYER	-	-	-	34,16,16	1808
FLATTEN	-	-	-	8704	0
DROPOUT 0.25	-	-	-	8704	0
DENSE	-	-	-	2	17410

To implement the FNDCNN system, an eight neuro physiologically inspired Kernel were developed and these have different shapes and delays the input signals were 16 IID Poisson process with a 10 HZ of average firing rate, and to design these 16 neurons over about 40 minutes approximately at a 500 HZ sampling frequency and this will end by the 1.2 million by 16 matrix for the input data images Table1 [4]. The time steps are shown in Figure 12.

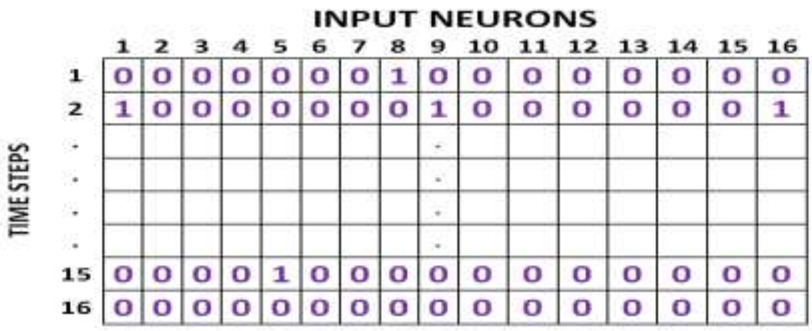

Figure12.Time Steps

The training phase starts after the completion of the construction of FNDCNN. While the training phase, the parameters of the convolutional layer and the self-organizing layer are stable. Only the FCL weights are regulated (tuned). This includes the fully connected output classification layer set into 0.25 softmax activation function with bias initialized to the zero. This model trained for 120 epochs each epoch consists of 58 iterations and it had approximately 23000 trainable parameters. The output is determined by the presence of spiking in the output neuron.

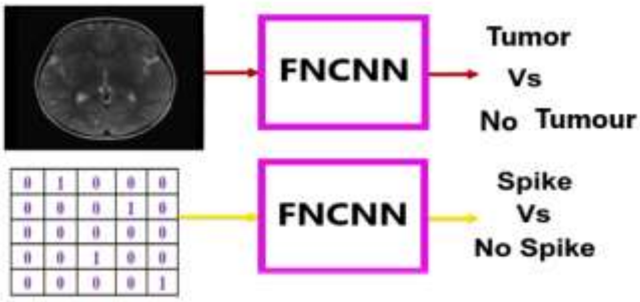

Figure 13. Output Spiking Activity

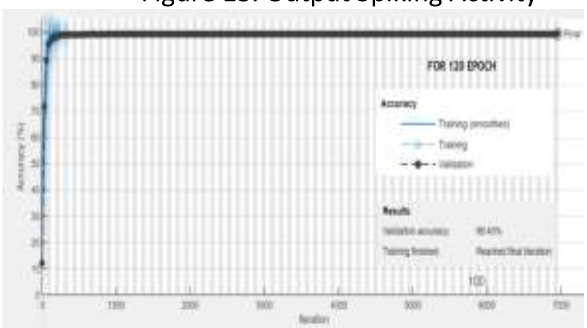

Figure14. Accuracy graph for 120 epochs

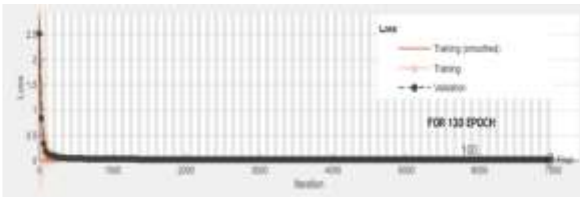

Figure 15. Loss graph for 120 epochs

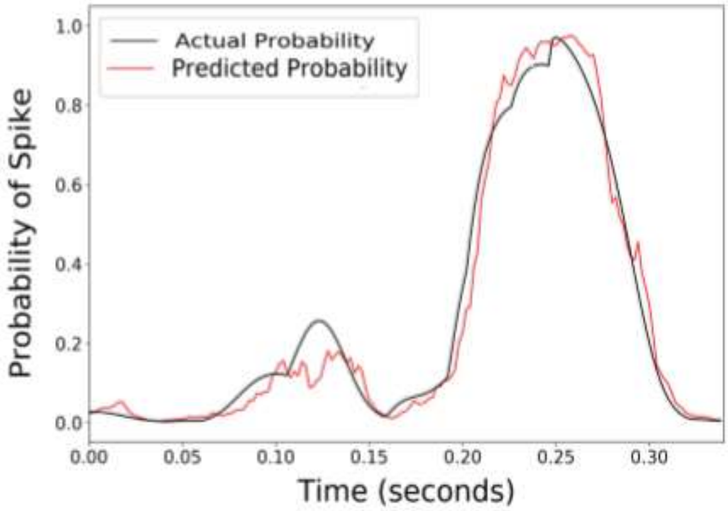

Figure 16.The Graph for the actual probability vs predicted probability

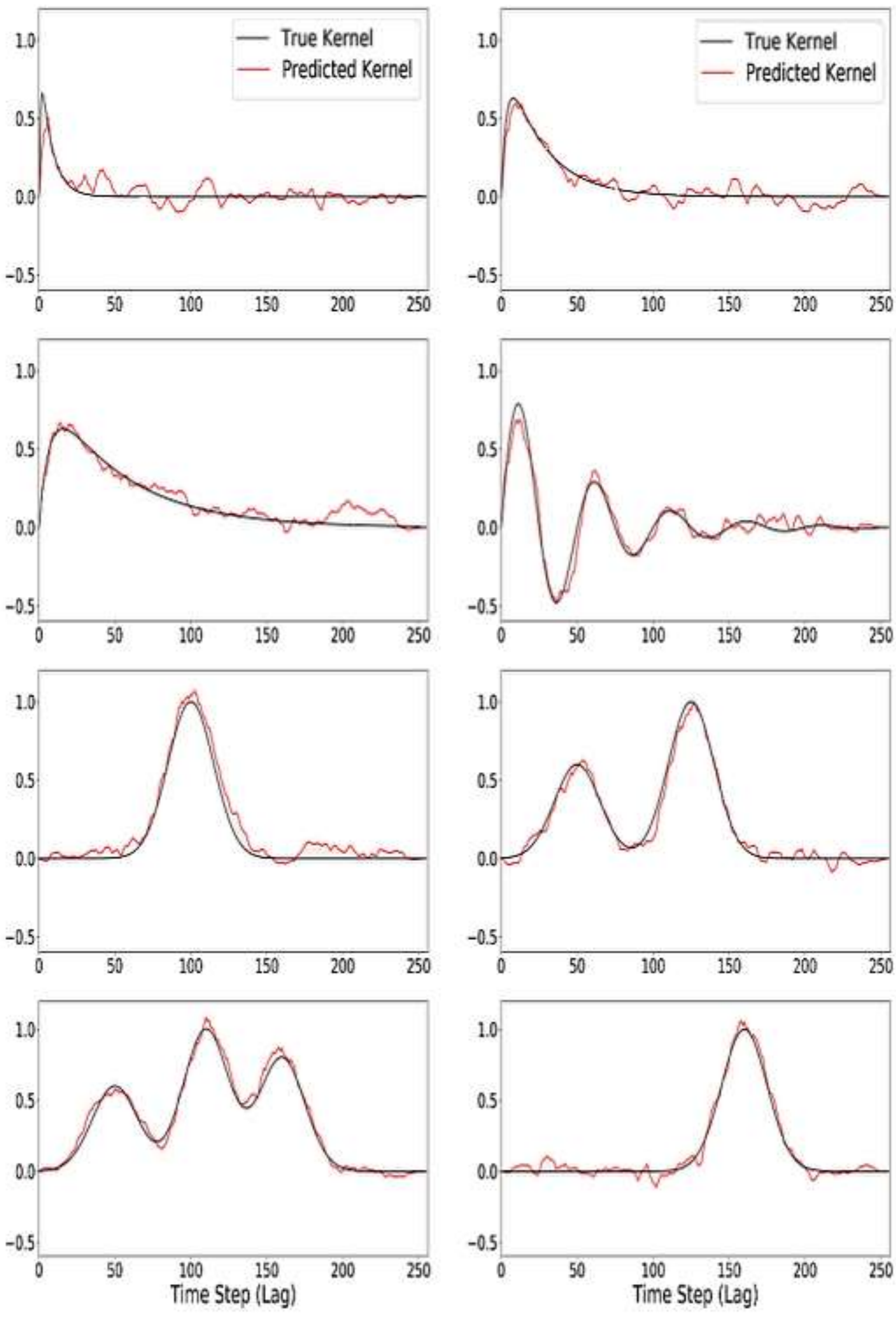

Figure 17.Generation of 8 Neurologically Inspired kernel

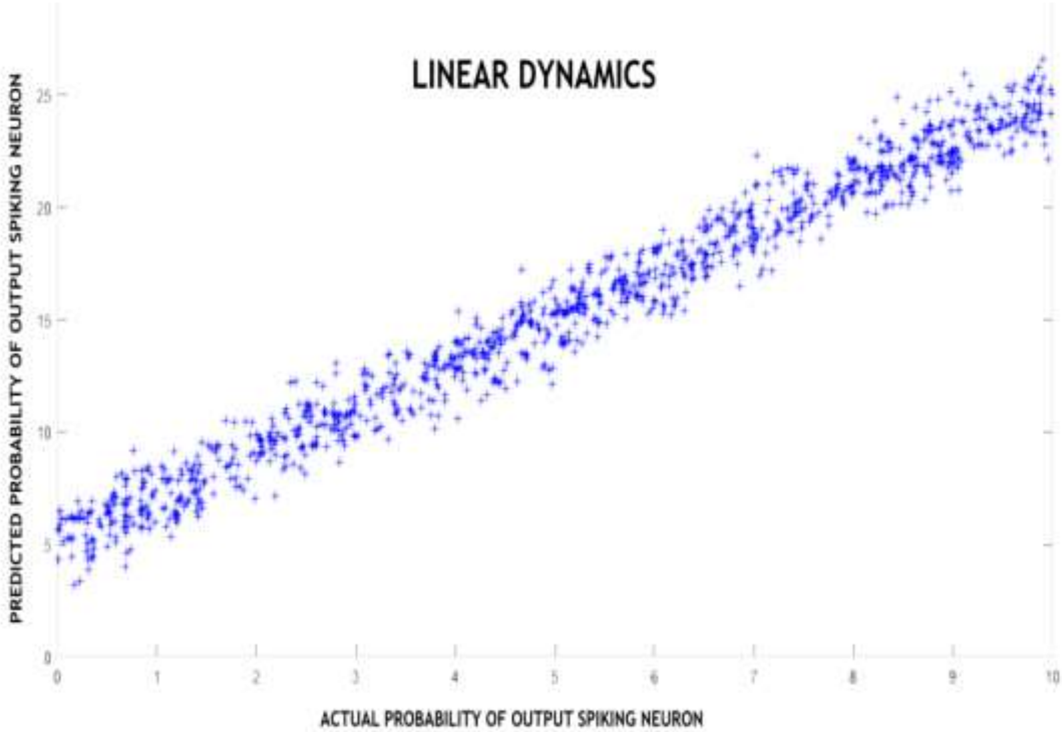

Figure 18. Linear Dynamics

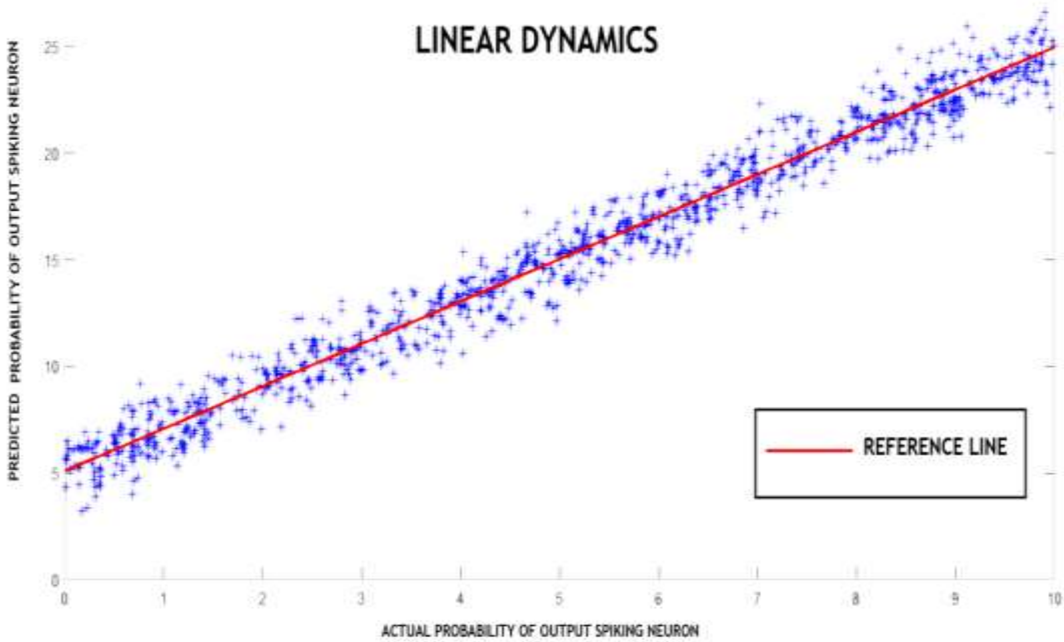

Figure 19. Linear dynamic with the reference line y = x

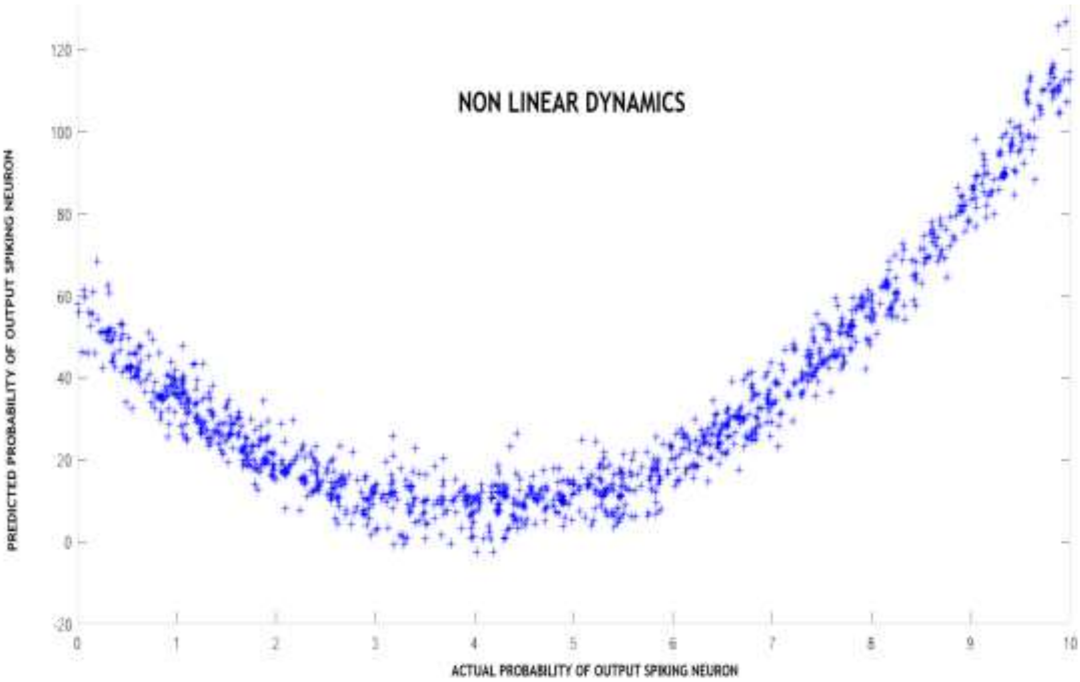

Figure 20. Non- Linear Dynamics

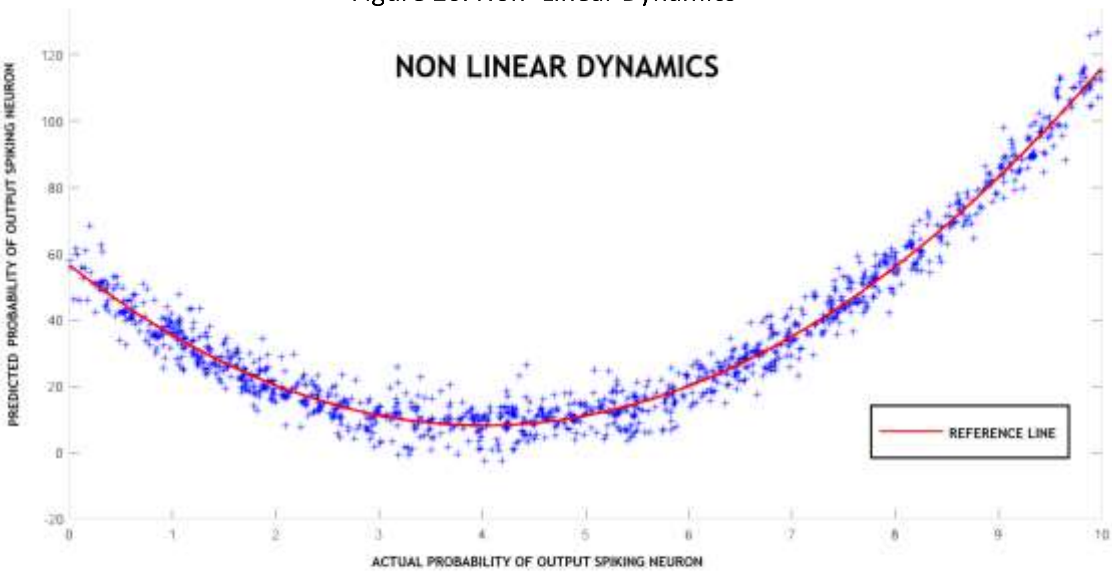

Figure 21.Non- Linear dynamic with the reference line $x^2 = 4ay$

The proposed system combines GFAM, CNN and fuzzy. The FNDCNN has been checked with FIVE performance metrics to evaluating the models:

1) The proposed model increase, high correlation between predicted and actual probability of output neural spiking (Figure 13) which reduces the Normalized Root Mean Square Error (NRMSE) up to 0.236

2) The result FNDCNN gives accuracy of 99.40% (Figure 14) than the traditional method of image classification.

3) The capturing both linear and nonlinear dynamics (Figure 18,19,20,21).

4) Generates the eight neuro physiological kernels (Figure 17).

5) Implements the detection of Gliblastoma Multiformae (shown in Figure 16)

Accuracy:
The accuracy define the system how accurate predicts the desired output. This system calculates the accuracy during the training of FNDCNN. This system achieves the highest accuracy of 98%. The comparison of accuracy shown in below table 2

Table2: Accuracy comparisons

TEST CASE	ACCURENCY
Micronet	91.20%
GLM+CNN	94%
FUZZY+CNN	96%
GFAM+CNN +FUZZY	98%

Correlation Coefficient

The probability of correlation coefficient (P_r or ρ) is used to measure the strong correlation between the probability of predicted and the actual neural spiking activity (i.e. two variables) in the FNDCNN system. The correlation coefficient is inversely propositional to the NRMSE. The FNDCNN has successfully achieved the high correlation it's automatically increased the accuracy by reducing the NRMSE and tabulated the comparison in the table 3 various correlation coefficient of different model with FNDCNN. This can be calculated using the equation 4.1 to 4.3.

$P_r (X,Y)=cov (X,Y) / \sigma X$ (4.1)

$Cov(X,Y) = 1/ n \sum^{n}_{i=0} (x_i - x^{\wedge}) * (y_i - y^{\wedge})$ (4.2)

$\sigma X = \sqrt{(1/ n \sum^{n}_{i=0}(x_i - \mu))}$ (4.3)

Where cov (X,Y) = covariance of x,y, σX = standard deviation, x_i =i^{th} value of x. y_i=i^{th} value of x, $x^{\wedge}$ =average value of x.$y^{\wedge}$=average value of y.n = total number of variables.μ = averagetotal number of variables. 7060

Table 3 Correlation comparison

TEST CASE	CORRELATION COEFICIENT (%)
Micronet	88
GLM+CNN	89
FUZZY+CNN	80
GFAM+CNN +FUZZY	92

Normalized Root Mean Square error (NRMSE)

Normalized Root Mean Square Error (NRMSE) is a frequently used *measure* of difference between actual values and predicted value The NRMSE facilitates the comparison between models with different scales. The systems with high NRMSE have the high over fitting. This FNDCNN reduce the normalized RMSE (NRMSE) (relates the RMSE to the observed range of the variable) which reduce the over fitting of the entire system. Thus, the NRMSE can be interpreted as a fraction of the overall range that is typically resolved by the model. The RMSE is the square root of the variance, known as the standard deviation.

$$NRMSE = RMSE / y_{max} - y_{min} \quad (4.5)$$

$$RMSE = \sqrt{\sigma X} \quad (4.6)$$

Table: 4.4 NRMSE Comparisons

TEST CASE	NRMSE
Micronet	0.249
GLM+CNN	0.254
FUZZY+CNN	0.458
GFAM+CNN +FUZZY	0.236

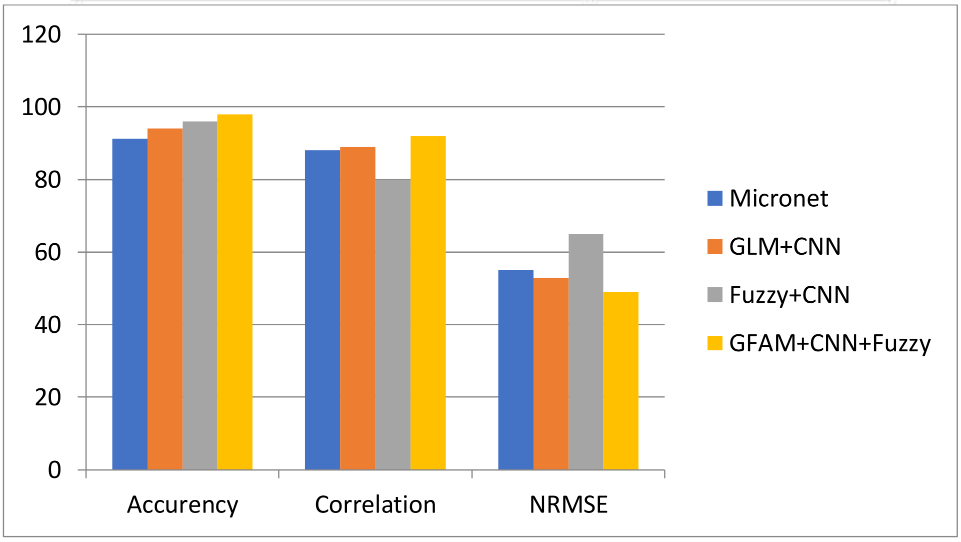

Figure:21 comparison chat

Figure 22 Detection of Glioblastoma Multiformae

V.CONCLUSION & FUTURE SCOPE

The proposed novel deep learning FNDCNN method was designed, tested and also compared with the already reported recent other methods in this paper. It improves the correlation between predicted and actual probability of output neural spiking as well as reduces the Normalized

Root Mean Square Error (NRMSE) up to 78.42%. The result reveals that the proposed MIMO system exhibits a superior performance than the conventional CNN, Micronet, and GFM. Furthermore, the proposed FNDCNN model ensures the 98% of accuracy to predict the output neural spiking from the input neural spiking. Thus, the proposed system can be used as assistive technology and aid the neurosurgeon and the radiologists. Indeed, serving as the candidate for programming a variety of brain-computer interfaces the complexity of the human brain can be bridged up by this CNN regarding the way that convolution operation is applied.

The proposed system can be integrated with cloud and live input to make it an open-source in the future. The application of the proposed system can be extended to the 3D images for higher-order kernel systems for improving the classification result and overall accuracy. There is a scope for improving the proposed system performance with a more extensive and diverse dataset, increase in the number of hidden layers, and also incorporating fine-tuning and transfer learning approaches.

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AUTHORS:

P.Nancy is working as an Assistant Professor in JP College of Engineering, Tenkasi. Completed her Doctorate in Information and Communication Engineering, MIT, Anna University Chennai. She received her M.E in Computer Science and Engineering in Dr.Mahalingam College of Engineering and Technology in the year 2012 and B.E in Computer Science and Engineering from Karunya University in the year 2010. She Published more than 15 National and International Conference. Her area of interest includes Wireless Sensor, Network Security Networks, Machine Learning and Deep Learning.

Angel BenRoja T.M is currently completed her B.E. in JP College of Engineering Tenkasi. She was award the best out going students for the year 2022. Her research areas includes Deep Learning and Machine Learning

Dr.E.A.Mohamed Ali is working as Professor Head in the Department of Computer Science and Engineering, JP College of Engineering, India. He received B.E. (Electrical and Electronics Engineering) from Manonmaniam Sudaranar University, India in 2000. He received his Master of Engineering degree in Applied Electronics from Madurai Kamaraj University, India in 2001 and received his Ph.D. from Anna University, India in 2020. His current area of research are Process System Engineering, Hybrid Vehicle System, Signal and Image Processing. He has published more than 30 papers in National and International Journals and conferences.