Neural Network-Based Automatic Classification of ECG Signals with Wavelet Statistical Characteristics

Arjun Choudhary[1], Dr. Kalpna Sharma[2] & Dr. Prakash Choudhary[3]

[1]Research Scholar, Computer Science Department, Bhagwant University, Ajmer, Rajasthan-305001, India
[2]HOD & Assistant Professor, Computer Science and Engineering Department, Bhagwant University, Ajmer, Rajasthan-305001, India
[3]Assistant Professor, Computer Science and Engineering Department, National Institute of Technology Hamirpur, HP-177005, India

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Abstract - *Cardiac abnormalities are the most common threat to human life. An electrocardiogram is the most common way to examine a heart abnormality. We present automatic detection of two types of ECG signals with statistical wavelet features using a Multilayer Perception Neural Network as the classifier. The database used for the heart abnormality detection is the MIT-BIH arrhythmia database. The Butterworth and Chebyshev Type-II filters have been introduced for de-noising the signal. The wavelet features have been extracted from the preprocessed ECG signal by using DWT (discrete wavelet transform) and 3600 samples have been taken from each signal and split into frames. The total number of samples of the signal is split into 4 windows, and each window contains 900 samples. DWT is applied in each frame or window to get wavelet coefficients which determine the characteristics of the signal. This wavelet coefficient is the input feature of the classifier for training and testing the model, which gives up to 100% accuracy for normal cases and 90% abnormality detection. This has been achieved.*

Key Words: MIT-BIH Arrhythmia, DWT, ECG, LDA, MLP, Chebyshev Type-II, Neural Network, Perceptron.

1. INTRODUCTION

There are mainly three sorts of components within the ECG signals. Each wave contains different information, which has includes amplitudes, durations, and morphology. Then High blood pressure, cholesterol, smoking, being overweight, etc. are the various causes that increase the general risk of heart disorder. During long-term monitoring, an automatic analysis of the ECG signal is vital to classify the various diseases of the heart. Manually analysing an oversized amount of information could be a very time-consuming task for doctors and analysts. Hence, there's a necessity for computational methods and machine learning techniques for the classification of the ECG signal. ECG analysis tools require knowledge of the location and morphology of the varied segments in the ECG recordings [1], [2].

Karpagechilvi et al. [3] proposed a sentimental analysis method where it's necessary to extract vital information from the ECG signal to detect new features for his use as an input within the artificial neural network to classify the ECG signal. In past studies, many researchers have worked with the ECG signal to detect the heart disorder. Several algorithms are been developed for the classification of ECG signals.

Stalin Subbiah et al. [4] proposed a method for preprocessing to cancel the noise using Gaussian filters, median filters, FIR-filters, and Butterworth filters. These are used for feature extraction, wavelet transformation, and QRS component features are used as a classifier input to spot the conventional and abnormal heartbeat.

Eduardo Joseda S. Luz et al. [5] performed research by which a way is proposed which uses a 10 sec ECG signal for normal and arrhythmia or abnormal ECG classification. The database has been taken from the MIT-BIH normal sinus database and supraventricular arrhythmia database.

Sharma and Bhardwaj et al. [6] proposed the model to train the neural network. The Levenberg-Marquardt function is used with 100% accuracy for the normal Sinus Database.

Ayub, J.P. Saini et al. [7]. Research performed by him uses the ANFIS (Adaptive Neuro-Fuzzy Interface System) model to identify normal and abnormal ECG signals. The MIT-BIH normal sinus and MIT-BIH supraventricular databases are used for training and testing the neural network. A feed-forward and back-propagation algorithm are accustomed minimise the errors, and a trapezoidal member function is employed as an input and output.

Mondal, S., Choudhary, P., et al. [8] used this MIT-BIH normal sinus database. The records from the MIT-BIH Arrhythmias and Apnea ECG databases from Physionet are used for training and testing our neural network based classifier. From which 90% healthy and 100% abnormal records are detected within the MIT-BIH Arrhythmias database with an overall accuracy of 94.44%. Within the Apnea-ECG database, 96% of normal and 95.6% of abnormal ECG signals are detected, achieving a 95.7% classification rate. From this MIT-BIH normal sinus database, 18 samples are taken and 61 samples are taken for abnormalities to train and test the model. The proposed model gives an accuracy of 100% for normal and 91% for abnormal.

Kulkarni and Lale et al. [9] proposed his work for extracting the morphological and statistical features like RR interval heart rate, arithmetic mean, median, variance, skewness, and kurtosis, respectively, for ECG analysis using discrete wavelet transformation (DWT). He proposed classification of the ECG signal with the KNN classifier, which is to be used to achieve a classification accuracy of 86.95%. The sensitivity and specificity results of ECG are 87.09% and 86.66%, respectively.

The inability to pick features using the correct feature extraction technique could be a significant disadvantage for ECG classification. To beat the matter, a window method is employed for applying the discrete wavelet transform and extracting statistical features for every window.

2. TRANSFORMATION OF DISCRETE WAVELETS

Wali, Mousa K and colleagues et al. [10]. DWT is that the mathematical tool used for various signal and image processing applications, which are employed in both continuous and discrete-time signals. It's used for de-noising the signals and have feature extraction techniques. It's made from variety of filter series (high pass and low pass filters) similarly as sub-sampling.

They proposed a multilevel task that's distributed using DWT. We have two styles of coefficients in each level: approximation coefficients and detail coefficients, which are obtained after DWT is applied to the preprocessed signal. These approximation coefficients contain a low-frequency component, and also the detailed coefficients contain the high-frequency components. The approximation coefficient continuously passes through the varied filters until the specified level of decomposition has been achieved or reached.

For ECG signal classification, LDA and MLP classifiers were proposed. During this case, the electrocardiogram signal may contain non-stationary characteristics. Hence, efficient and instantaneous separation of the ECG rhythms is often done supported on the decomposition of the EEG signals into wavelet coefficients. The Wavelet transform may be a powerful spectral estimation technique for the time-frequency analysis of a signal. Commonly, Haar wavelets, Daubechies wavelets, coeiflets, etc., with various different wavelet families are used. During this study, Dabechies (DB) wavelets are used.

3. METHODS

The task of classification for ECG signals is broadly divided into three parts: preprocessing, feature extraction, and classification. Fig. 1. shows the tectic during this work.

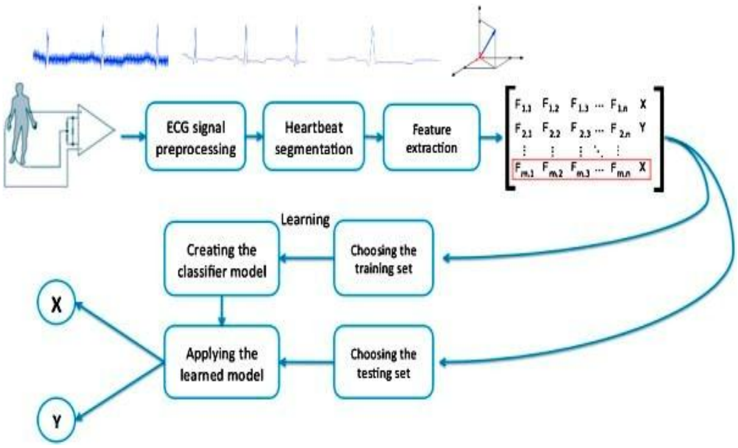

Fig. 1. Multidimensional diagram of the ECG classification.

3.1 Datasets

The database provided by MIT-BIH Arrhythmia is from Physionet ATM [13]. The database contains 48 recordings, including male and female. Each recording is half-hour long and sampled at 356 Hz.For the classification of ECG signals, a 10-second duration signal has been used and split into two parts: normal and arrhythmia (or abnormal).

3.2 Preprocessing

In the electrocardiogram (ECG) signal, various styles of noises are present, like baseline drift noise, power cable noise, electrode contact noise, and other kinds of noises. Hence, this stage is extremely vital for ECG signal processing. To get rid of the noise, we use the band-pass filter, the Butterworth filter, and the Chebyshev Type-II filter designed for this work. The frequency of the ECG signal is in-between 0.5 Hz and 100 Hz. It's necessary to preprocess the ECG signals before performing feature extraction and classification to urge higher accuracy.

Sonal K et al. [14] used Butterworth to get rid of baseline drift noise. Chebyshev Type-II filters are wont to remove higher frequencies. Fig. 2 and Fig. 3 show the raw and pre-processed ECG signals, respectively.

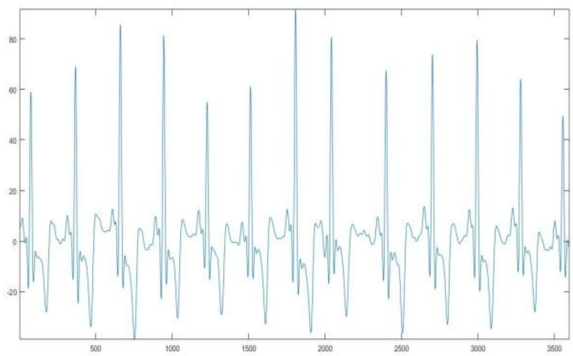

Fig. 2. Unfiltered ECG signals

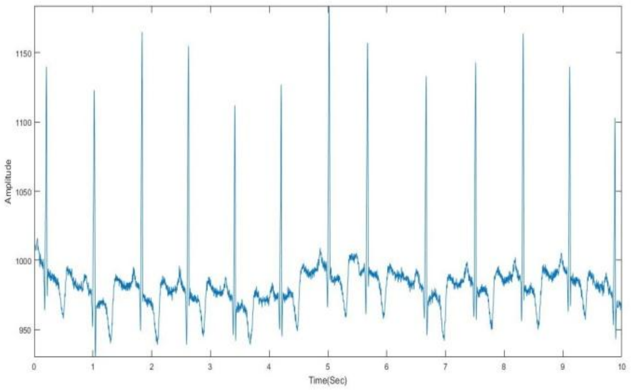

Fig. 3. Baseline wanders removal and filtered signals.

3.3 Extraction of Characteristics

The process of feature extraction is extremely important for the classification of ECG signals. Within the first start, the features are extracted from the preprocessed ECG signal using DWT (Discrete Wavelet Transformation) using 10 seconds of ECG signal from the MIT-BIH Arrhythmia database [15]. The desired statistical features are extracted from the DWT coefficient. The extracted features are as follows: • Energy • Entropy • Mean • Median • Standard Deviation In this study, the features are extracted using DWT. The wavelets used are Daubechies (db3), which are applied to the 3600 samples for the 10 second ECG signal and divide the signal into 4 windows of equal samples, 900 samples per window. The DWT is performed out at four levels to get the detailed and approximate coefficients. From each window, 20 statistical features are calculated to represent the ECG signal [16].

3.4 Classification

This is the ultimate step where the ECG signals are recognized with the assistance of a classifier. The extracted features are the inputs of the classifier to spot the conventional and abnormal ECG signals. A neural network (NN) classifier is employed during this work. Within the next section, the classification process is described [17].

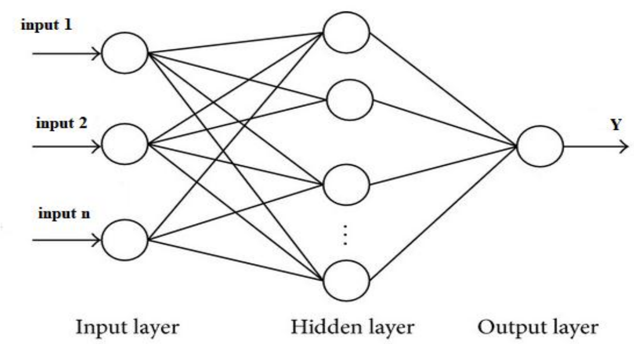

Fig. 4. The three-level tree of DWT.

4. NEURAL NETWORK

A multi-layer perceptron (MLP) neural network classifier is used as a classifier to check the features of two types of signals [18] and [21]. A multi-layer perceptron (MLP) could be a class of feed-forward artificial neural network (ANN). Sometimes the term "MLP" is employed ambiguously to mean any feed-forward ANN, but sometimes it strictly refers to networks composed of multiple layers of perceptrons (with threshold activation). Multilayer perceptrons are sometimes co-laterally stated as "vanilla" neural networks after they have a one hidden layer [22]–[26]. 1. As proposed by Atangana et al. [27], a selected problem is that an artificial neural network consists of three layers of neural networks: input, output, and a hidden layer. The neural network first trains the network by training the information to search out the link or relationship between the features of the ECG signal and therefore the properly trained algorithm. The trained algorithm is employed as a back-propagation algorithm with the connection of weights between layers. The algorithm calculates the mean square error, during which the minimum mean square error is chosen to differentiate between the two varieties of ECG signals.

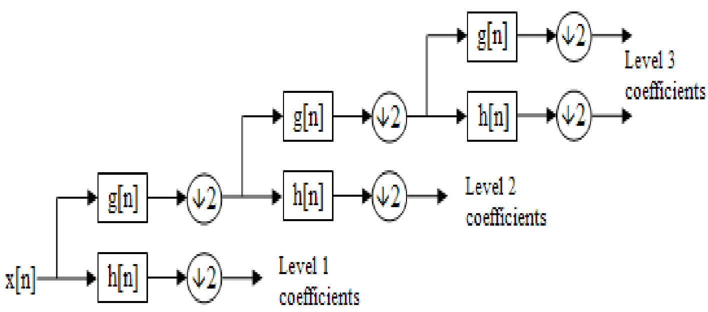

Fig. 5. The architectural model of MLP.

Multi-layer perceptrons are designed to make approximations of any continuous function and may solve problems that are not linearly separable. The foremost uses of MLP are pattern classification, recognition, prediction, and approximation. The computations going down at every neuron within the output and hidden layer are as follows:

(1) Ox = Gb2 + W2hx

(2) Hx = x = sb1 + W1x

With bias vectors b(1) and b(2), weight matrices W(1) and W(2), and activation functions G and s, The parameters are

W (1), b (1), W (2), b (2)

Typical choices for s include the Tanh function with

Tanh (a) = (e^{a} e^{a}) or (e^{a} + e^{a})

The logistic sigmoid function, with

Sigmoid (a) = 1/1 (+ e^{a}).

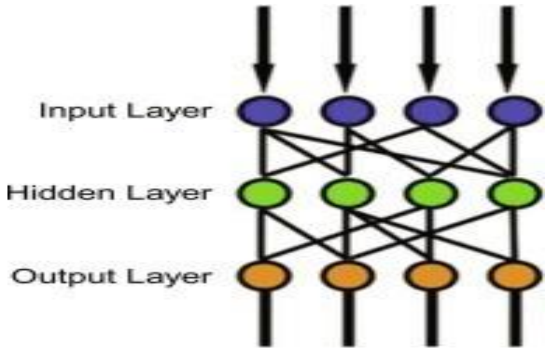

Fig. 6. Schematic representation of a MLP with a hidden layer

MLPs are neural network models that work as universal approximators, i.e., they'll approximate any continuous function. The above MLP is composed of neurons, which are called perceptions. So, before explaining the overall structure of MLPs, the overall structure of a perceptron is going to be explained. As shown in Figs. 6 and 7, A perceptron receives n features as input (x = x1, x2,... xn), and every of those features is related to a weight. Input features must be numeric. So, non-numeric input features should be converted to numeric ones so as to use a perceptron. A categorical feature with p possible values is converted into p input features representing the presence or absence of these values. These are called dummy variables. For instance, if the input feature of the event type can take the worth of recent development, enhancement, or re-development, it may well be replaced by the three dummy variables of new development, enhancement, and redevelopment, which take the value of 1 if the corresponding value is present and 0 if it's absent.

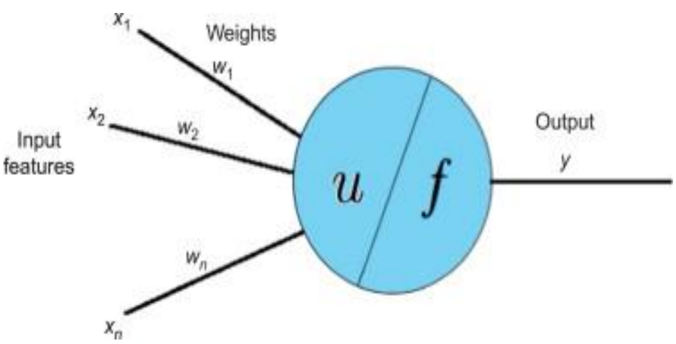

Fig. 7. Perceptron Schema with N input features

The input features are passed to the input function u, which computes the weighted sum of the input features:

$1nw_ix_i$ u(x) = I

The result of this computation is then passed onto an activation function *f*, which will produce the output of the perceptron. In the original perceptron, the activation function is a step function:

If u(x) > 0, Y = f(u(x)) = 1, otherwise,

Where i, is a threshold parameter.

An example of a step function with a value of 0 is shown in Figure 24.2a. Thus, we can see that the perceptron determines whether $w_1x_1 + w_2x_2 + + w_nx_n > 0$ is true or false. The equation $w_1x_1 + w_2x_2 + + w_nx_n = 0$ is the equation of a hyperplane. The perceptron outputs 1 for any input point above the hyperplane and 0 for any input on or below the hyperplane. For this reason, the perceptron is named a linear classifier, i.e., it works well for data that is linearly separable. Perceptron learning consists of adjusting the weights so a that a hyperplane separates the training data that 's determined.

5. RESULT WITH DISCUSSION

In this study, the MIT-BIH Arrhythmia database has been used, from which 45 records were taken of 10 second signals of 3600 samples [13], [15]. The above datasets are first preprocessed using a Chebyshev type II filter to cancel various types of noise. Then the preprocessed signal is divided into windows, where each window contains 900 samples. Then, for feature extraction, a discrete wavelet transform was applied in each window, and we obtained 20 attributes. A total of 80 attributes are obtained from all windows to represent the ECG signals. The statistical features that were extracted are the inputs of the artificial neural network. The database is separated into normal and abnormal classes. There are 25 and 20 records from normal and abnormal, respectively. Table 1. shows the total number of training and testing records used for the classification of ECG. It shows 100% accuracy for normal ECG subjects.

Types of Records	Total Records	Training Records	Testing Records	Accuracy
Normal	25	18	7	100%
Abnormal	20	10	10	90%

Table 1 shows the MIT-BIH Arrhythmia Database's training, testing, and accuracy.

6. CONCLUSION

In this experiment, the MIT-BIH arrhythmias database for 10 second signals of 3600 samples has been used for the classification of ECG signals, and the signals are partitioned into 4 windows, each of which contains 900 samples per window. Then, we extract some statistical features by applying a discrete wavelet transformation (DWT). The features that were extracted are energy, entropy, median, mean, and standard deviation, and these features are passed through the artificial neural network with a back propagation algorithm. The results show that 100% accuracy for normal ECG subjects and 90% accuracy for abnormal ECG subjects was achieved.

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REFERENCES

[1] Rashkovska A, Depolli M, Tomaic I, Avbelj V, Trobec R, (2020): Long-term monitoring with a medical-grade ECG sensor.Sensors, 20, 1695.

[2] Miquel Alfaras, Miguel C. Soriano, and Silvia Ortn (2019): A Fast Machine Learning Model for ECG-Based Heartbeat Classification and Arrhythmia Detection. http://doi.org/10.3389/fphy. 2019.00103.

[3] Karpagachelvi S, Arthanari M, Sivakumar (2010): ECG Feature Extraction Techniques-A Survey Approach. International Journal of Computer Science and Information Security, Vol. 8, No. 1.

[4] Subbiah S, P Rajkumar, and P Subbthai (2015): Artificial Neural Network and Machine Learning Approach for Feature Extraction and Classification in ECG Signal Processing.Vol. I. ISBN: 978-81-929742-5-5.

[5] Eduardo Joseda S. Luz, William Robson Schwartz, Guillermo Cámara Chávez, and David Menotti (2016): A survey of computer methods and programmes in biomedicine 127, 144–164.

[6] Sharma, A., and K. Bhardwaj (2015): Detection of normal and abnormal ECGs using a neural network.International Journal of Information Research and Review, Vol.2 (05), pp. 695-700.

[7] S. Ayub and J.P. Saini (2011): Using a cascaded forward neural network for ECG classification and abnormality detection. DOI: 10.4314/ijest.v3i3.68420.

[8] Sourav Mondal and Prakash Choudhary (2019): Detection of Normal and Abnormal ECG Signal Using ANN: Selected Revised Papers from the Joint International Symposium on Artificial Intelligence and Natural Language Processing (iSAI-NLP 2017). T. Theeramunkong, et.al.(2017).Advances in Intelligent Informatics, Smart Technology, and Natural Language Processing iSAI-NLP. Advances in Intelligent Systems and Computing, Springer, Cham. Vol. 807. https://doi.org/10.1007/978-3-319-94703-73.

[9] Kulkarni A, Lale S, Ingole P, and Gengaje S (2016): ECG signal analysis, SSRG International Journal of Electronics and Communication Engineering (SSRG-IJECE), Vol. 3. DOI: 10.14445/23488549/IJECE-V3I4P104.

[10] Wali, Mousa K et al. (2012): Development of a Dicerete Wavelet Transform (DWT) toolbox for signal processing applications, International Conference on Bionedical Engineering (ICoBE), Penang, pp.211-216, DOI: 10.1109/ICoBE.2012.6179007.

[11] S. Hemchandra and Y. Dileepkumar (2020): Realtime analysis of an ECG signal using the Discrete Wavelet Transform, International Journal of Advanced Science and Technology, Vol. 29.

[12] Romain Atangana et al. (2020): Djoufack/ publication/ 339789817. ECG Signal Classification using LDA and MLP.

[13] https://www.researchgate.net/profile/Laurent.

[14] http://www.physionet.org/physiobank/ database/mitdb.

[15] Sonal K Jagtap and Mahadev Dattatraya Uplane (2012): A Real-Time Approach to ECG Noise Reduction Using a Chebyshev Type II Digital Filter.49(9), International Journal of Computer Applications, DOI: 10.5120/7659-0763.

[16] https://archive.physionet.org/physiobank/database/html /mitdbdir/intro.htm.

[17] Muhidin A. Mohamed, Mohamed et. al. (2014): An approach for ECG Feature Extraction using the Daubechies 4 (DB4) Wavelet. Volume 96–No.12 of the International Journal of Computer Applications (0975–8887).

[18] Mohamed Hammad, Asmaa Maher, et. al. (2018): Detection of abnormal heart conditions using ECG signal characteristics.Pages 634-644 in Volume 125, September, https://doi.org/10.1016/j.measurement.2018.05.033.

[19] S. Abirami and P. Chitra (2020): Advances in Computers-The Digital Twin Paradigm for Smarter Systems and Environments: Industry Use Cases,

[20] Vijay Kotu and Bala Deshpande (2019): Data Science (Second Edition). K Gurney (2018): An introduction to neural networks.

http://www.macs.hw.ac.uk/~yjc32/project/refNN/Gurneyetal.pdf.

[21] Awaysheh, J. Wilcke, F. Elvinger (2019): Review of Medical Decision Support and Machine-Learning Methods. https://doi.org/10.1177/0300985819829524

[22] https://en.wikipedia.org/wiki/Multilayer perceptron.

[23] Flora Amato, Nicola Mazzocca, et.al. (2017): An Intelligent Model for Classification and Intrusion Detection, 31st International Conference on Advanced Information Networking and Applications Workshops (WAINA) DOI: 10.1109/WAINA.2017.134.

[24] https://towardsdatascience.com/multilayer-perceptron-explained-with-a-real-life-example-and-python-code-sentiment-analysis-cb408ee 93141.

[25] MW Gardnel, R Dorlingal (1998): Artificial neural networks (the multilayer perceptron)-A review of applications in the atmospheric sciences in Atmospheric Environment Vol.32, Issues 14–15, 1, Pages 2627–2636.

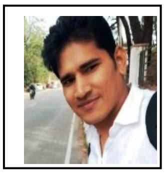
[26] Yildirim, P Pławiak, R S Tan and U R Acharya (2018): Arrhythmia Detection Using Deep Convolutional Neural Network With Long Duration ECG Signals. Computers in Biology and Medicine. DOI: 10.1016/j.compbiomed.2018.09.009.

[27] Romain Atangana, Laurent Chanel et.al.(2020): Formalized paraphrase EEG Signal Classification using LDA and MLP Classifiers, Health Informatics. An International Journal (HIIJ), Vol. 9, No. 1. Djoufack/publication/339785382. Mother Wavelet Selection for EEG Signal Analysis Frequency Band Decomposition and Discriminative Feature Selection/links/ 5ebda54492851c11a867 c14a.

BIOGRAPHY OF AUTHORS

1. Arjun Choudhary, Research Scholar, Computer Science Department, **Bhagwant University, Ajmer, Rajasthan-305001, India,** Place: Jodhpur (Rajasthan), DOB: 30-08-1976, Sr. Technical Assistant, Government Engineering College, Ajmer since 12 Dec. 1999 - till date and having 22 years of experience. Field of Research is Adhoc Networks, Document Image Analysis, Medical Image Processing, Computer Vision and Pattern Recognition, Machine Learning, Neural Networks and AI.

2. Dr.Kalpna Sharma, HOD & Assistant Professor, Computer Science and Engineering Department, **Bhagwant University, Ajmer, Rajasthan-305001, India, Place: Ajmer (Rajasthan),** 21st July ,2016 – till date. Assistant Professor, Pacific Institute of Management & Technology Pacific University, Udaipur (Rajasthan) 1st Jan. 2012 – 31st June 2013. Lecturer (IT) Savitri Institute of Management, Savitri Girls' College, Ajmer, Affiliated to Rajasthan Technical University, Kota, (Rajasthan) 1st Oct.2009 – 31st Dec.2011. Research experience in Document Image Analysis, Image Processing, Computer Vision and Pattern Recognition etc.



3. Dr.Prakash Choudhary, Assistant Professor, Computer Science and Engineering Department, **National Institute of Technology Hamirpur, Himachal Pradesh,Hamirpur, HP-177005, India,** Place: Hamirpur, HP. DOB: 01-01-1987, 21st Dec. 2018 – till date. HOD & Assistant Professor, National Institute of Technology Manipur, India-795004, 30th Dec.2013 – 20th Dec.2018. Research experience in Document Image Analysis, Bioinformatics, Algorithms in Distributed Systems, Medical Image Processing, Computer Vision and Pattern Recognition, Machine Learning and AI.