International Journal of Computer and Engineering Optimization (IJCEO)
Volume 04, Issue 02, March – April (2026)

RESEARCH ARTICLE

SPIKING NEURAL NETWORK-BASED NOMA-OFDM PROCESSING UNDER WEIBULL FADING FOR ACCURATE UPLINK SIGNAL PREDICTION

M. Sandhya[1,*], Aisha Banu Wahab[2], Arputha Rathina Xavier[3]

[1] Professor, School of Computer Science and Engineering, Vellore Institute of Technology, Chennai -600127.
[2] Professor, Department of Computer Science and Engineering, BSA Crescent Institute of Science and Technology, Chennai -600048.
[3]Associate Professor, Department of Computer Science and Engineering, BSA Crescent Institute of Science and Technology, Chennai -600048.
[*]*Corresponding e-mail: sandhyamagesh1997@gmail.com*

Abstract – Non-orthogonal multiple access (NOMA) approach has gained popularity in recent years. Additionally, it has shown promise as a technology for wireless communication systems up to and including the fifth generation (5G). In this paper a novel Spiking Neural Network-Based NOMA-OFDM Processing Under Weibull Fading for Accurate Uplink Signal Prediction has been proposed. In the offline stage, labeled NOMA-OFDM signals are passed through a Weibull fading channel to generate training data and corresponding labels, which are then used to train the SNN for accurate prediction. In the online stage, real-time NOMA-OFDM signals undergo the same Weibull fading channel effect, and the processed signals are fed into the trained SNN to produce predictions without requiring label information. This approach enables robust channel estimation and signal detection by leveraging the adaptability and learning capability of the SNN.

Keywords *– Non-orthogonal multiple access, fifth generation, Spiking Neural Network, Signal Prediction.*

1. INTRODUCTION

NOMA-OFDM which combines the multipath fading resistance of OFDM with the spectral efficiency benefit of NOMA, has been shown to be a viable multiple access strategy for next-generation wireless networks. By allowing several users to use the same time-frequency resources, NOMA-OFDM's power domain multiplexing capability can improve throughput and connection. For diverse user contexts and massive machine-type communications, this approach is suitable for 5G and beyond. But, in the case of many user signals being sent concurrently, complicated interference patterns are formed and channel estimate and reliable recognition of the signal becomes very difficult.

The recent advances of deep learning have proven to be very effective for addressing complex, nonlinear wireless communications problems. Conventional mathematical models can only take advantage of some features of the channel, and data-driven models, such as CNN and RNN, can effectively learn the characteristics of the channel and minimize the interference without relying solely on the conventional mathematical models. A NOMA-OFDM system with deep learning can enhance the recognition accuracy of the signals and the accuracy of the channel estimate under different fading conditions. This paves the way for hybrid approaches combining learning-based and model-based approaches for improved results.

Though model-based techniques can provide analytical insight, they often fail to deal with the highly dynamic and nonlinear nature of real-world wireless channels. However, solely data-driven methods could have problems with generalisation and need large training datasets. The advantages of both approaches may be successfully combined in a hybrid deep learning framework, which uses neural networks to address model defects and physical models to direct learning. For multiuser uplink scenarios in NOMA-OFDM systems, when channel recovery and interference cancellation are crucial, this method shows the most promise.

Inter-user interference, frequency-selective fading, and noise distortion continue to make accurate CE and signal identification challenging in multiuser uplink NOMA-OFDM models. Traditional estimation methods, such as LS and MMSE, usually show performance degradation in highly dynamic channels. Furthermore, successive interference cancellation (SIC), NOMA's principal detection method, is very vulnerable to estimation errors, resulting in error propagation. As a result, there is an urgent need for an intelligent, hybrid DL model that can perform channel estimations and signal detection simultaneously while being resilient, simple, and adaptive to changing channel conditions. The major contribution of the work has been followed by

- The primary objective is to develop a hybrid offline–online framework for efficient NOMA-OFDM signal processing.
- To simulate realistic wireless environments using Weibull fading channel modeling for improved channel estimation performance.
- To integrate a spiking neural network for adaptive and low-complexity signal prediction in dynamic conditions.
- To achieve robust joint channel estimation and signal detection in multiuser uplink NOMA-OFDM models.

The remainder of the work is divided into sections: section 2 represents the literature study, section 3 depicts the suggested technique, section 4 represents the results and discussion, and section 5 illustrates the conclusion of the proposed model respectively.

2. LITERATURE REVIEW

In 2022 Rahman, M.H., et al., [14] suggested a DNN with BiLSTM for signal identification of the first sent signal and multiuser uplink channel estimate (CE). The suggested model's performance is compared in the simulation results with that of the CNN methodology and conventional CE methods like MMSE and LS. The suggested approach is demonstrated to offer workable gains in signal-to-noise ratio and symbol-error rate, making it appropriate for 5G wireless communication and beyond.

In 2022 Gaballa, M., et al., [15] investigated the use of a Deep Neural Network (DNN) to explicitly estimate the channel coefficients of each user in the NOMA cell. Following a thorough mathematical examination of the optimisation problem, the optimal power factors are found using the Lagrange function and KKT criterion. When comparing the suggested DL model-assisted NOMA to the conventional NOMA approach, the simulation results in terms of BER, outage probability, sum rate, and individual capacity demonstrate that consistent performance can be attained even when cell capacity rises.

In 2023 Panda, B. and Singh, P., [16] proposed deep convolutional-long short-term memory (ConvNet-LSTM)-assisted receiver for signal identification in downlink NOMA systems. The proposed technique uses implicit channel state estimation to directly obtain the broadcast symbol. Furthermore, the suggested deep ConvNet-LSTM technique's robustness and superiority over previous methods are assessed.

In 2021 Xie, Y., et al., [17] created a receiver with DL assistance to identify NOMA joint signals. In end-to-end mode, the DL-based receiver simultaneously performs equalisation, demodulation, and channel estimation. When compared to the conventional signal identification approach for the NOMA scheme, the suggested deep learning strategy demonstrates a decent improvement in performance and resilience using the tapped-delay line (TDL) channel model, which is used in the 5G communication environment.

In 2022 Pandya, S., et al., [18] created a NOMA-OFDM system based on DNN to decipher the user's signals. First, training is done on the deep neural network. The simulation findings demonstrate that the deep neural network will learn the channel state information through data testing and is more resilient to symbol distortion brought on by inter-symbol information.

In 2020 Chuan, L.I.N., et al., [19] presented a CNN strategy to recover the intended signal that had been hampered by the MIMO channels. The proposed scheme can directly recover the information of a large number of users from a cluster without going through the traditional communication signal processing process, especially in the uplink NOMA scenario. The results of simulation studies in the Rayleigh channel show that the suggested learning system works better in terms of error performance than the traditional SIC detection method.

In 2020 Sim, I., et al., [20] proposed a CNN-based SIC approach to improve the multiuser and single base station NOMA schemes' performance. The suggested CNN-based SIC system can reduce the losses brought on by the SIC's flaws, in contrast to the current SIC systems. The simulation results show that the CNN-based SIC strategy may achieve good detection performance and successfully overcome the drawbacks of the traditional SIC.

3. PROPOSED METHODOLOGY

In this section a novel Spiking Neural Network-Based NOMA-OFDM Processing Under Weibull Fading for Accurate Uplink Signal Prediction has been proposed. In the offline stage, labeled NOMA-OFDM signals are passed through a Weibull fading channel to generate training data and corresponding labels, which are then used to train the SNN for accurate prediction. In the online stage, real-time NOMA-OFDM signals undergo the same Weibull fading channel effect, and the processed signals are fed into the trained SNN to produce predictions without requiring label information. This approach enables robust channel estimation and signal detection by leveraging the adaptability and learning capability of the SNN. Figure 1 illustrates the proposed methodology.

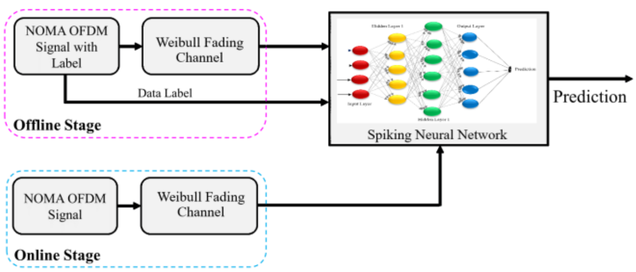

Figure 1 Proposed Methodology

3.1 Weibull Fading approach

In wireless communication systems, the Weibull fading channel is a statistical model that is used to depict small-scale fading, particularly in settings where the fading intensity is lower than that of Rayleigh fading. It is characterized by a shape parameter β (fading severity) and a scale parameter Ω (average power). The Weibull distribution is versatile and can model fading channels with different tail behaviors by adjusting β.

$$f_R(r) = \frac{\beta}{\Omega}\left(\frac{r}{\Omega}\right)^{\beta-1} \exp\left[-\left(\frac{r}{\Omega}\right)^{\beta}\right], r \geq 0 \quad (1)$$

β>0 is the shape parameter (fading severity) and Ω>0 is the scale parameter related to the average received power. r is the instantaneous amplitude of the fading envelope. The Weibull fading model is useful in NOMA-OFDM analysis because it allows more flexibility in modeling practical channels where fading may not strictly follow Rayleigh or Rician distributions.

3.2 Spiking Neural Network

It is a network model that integrates time with neuronal and synaptic states and progressively analyses every natural neural structure. Depending on the circumstances, the activation of a neurone can alter the signal potential of neighbouring neurones. By employing a certain threshold, it activates neurones. Each brief signal that arises in the model is taken into account by spiking neurones, but they do not immediately respond to it. As soon as this happens, spiking neurones start processing the signal, which necessitates crossing a certain threshold. As a result, it generates an output signal that is either rising or dropping. Equation (2) displays the integral formula utilised in the LIF technique. I stands for current, V for voltage, C for capacitor, R for resistance, and t for time value in this equation.

$$\mathrm{I}(t) - \frac{V_m(t)}{R_m} = C_m \frac{\partial V_m(t)}{\partial t} \quad (2)$$

Although SNNs are more complicated structures than artificial neural networks (ANNs), both models have similarities. ANNs feature continuous outputs. As an alternative, it produces an incomprehensible binary output. Ultimately, it shows that each neurone only takes into account its neighbours and increases the spatial learning of spiking neurones. The neural network with spiking is shown in Fig 2.

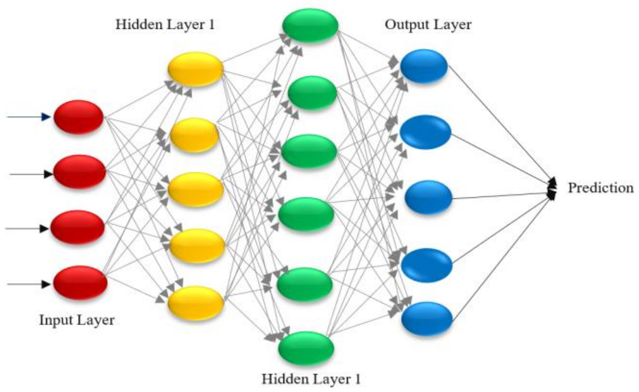

Figure 2 Architecture of Spiking Neural Network

The SNN model goes through a difficult and intricate training procedure and learns when characteristics spread across hidden layers. The last layer, which consists of completely connected layers, is where classification occurs. One popular classification technique is the Softmax function. The learnt features make use of the Softmax approach and hot coding. Every feature in hot coding has a matching class. The Softmax method is used to assign probability values to the attributes supplied to the output layer.

$$y_i = \exp(a_i) \sum_j \exp(a_j) \quad (3)$$

Spiking neural networks are built on discrete, spiking neuronal events that occur across intervals, whereas conventional neural networks emphasise intervals rather than producing values.

$$f_x(x') = R_{max} e^{\frac{\cos(\frac{2\pi}{N}(XX))}{\delta^2}} \quad (4)$$

N is the number of neurones in equation (4), where x is the input layer and y=f(x) is the output layer. In the XX coordinate, $R_{max}$is the firing rate and the number of neighbouring neurones. δ stands for a constant value.

4. RESULT AND CONCLUSION

The experimental investigation was carried out using Spyder, an Anaconda navigator operating on Windows 10 with an Intel i3 CPU clocked at 2.10GHz and 8GB RAM.

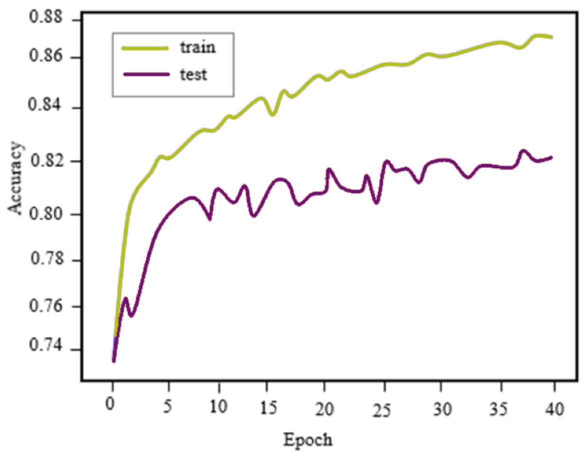

Figure 3 Training and evaluating the suggested method's accuracy

Figure 3 displays a model's accuracy throughout 40 epochs for both training and testing. The training accuracy shows constant learning, beginning at about 0.74 and increasing progressively to reach about 0.87 at the end of the era. Additionally, the testing accuracy increases quickly in the early epochs, stabilizing around 0.82 with little oscillations, indicating strong generalization with modest alterations brought on by noise or the complexity of the dataset.

Figure 4 illustrates the model's performance over 40 epochs for both training and testing datasets. The training loss starts near 0.62 and decreases steadily to around 0.28, indicating effective learning and improved fit to the training data. The testing loss also shows a downward trend that plateaus at a higher value (~0.42) with some fluctuations that may be attributed to the fluctuations in the test data set or slight overfitting.

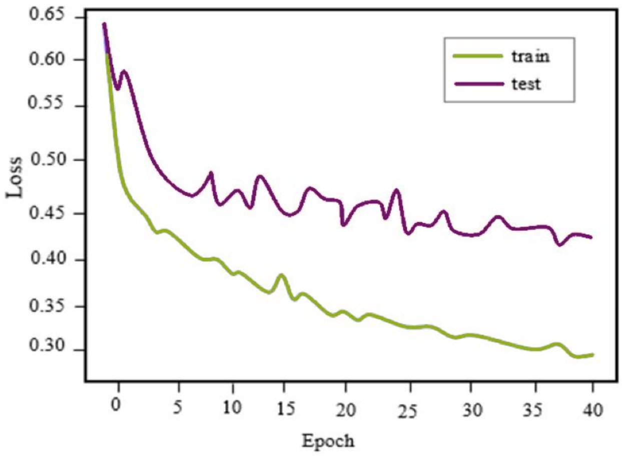

Figure 4 Training and Testing loss of proposed method

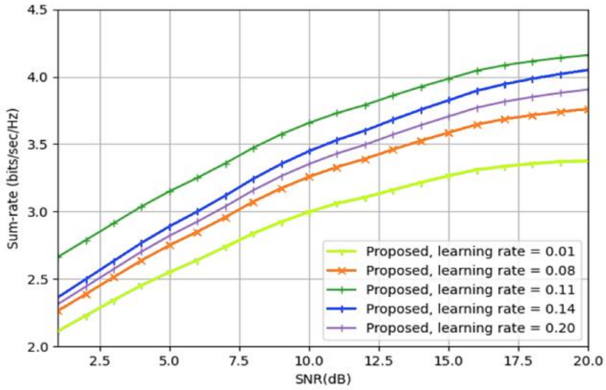

Figure 5 Sum rate versus SNR for the proposed model

Figure 5 shows the sum-rate performance in bits/sec/Hz versus SNR in dB of the proposed system for different learning rates. For all configurations, the sum-rate increases as SNR increases from 2 to 20 dB, suggesting that increasing SNR results in more data being transmitted. The learning rates that yield the best overall results are 0.11, 0.14, and 0.20, which are very close, with 0.01 producing the least desirable results. The trend indicates that having an optimal learning rate is highly beneficial for the sum-rate efficiency in the proposed framework, more particularly in moderate-to-high SNR regions.

Figure 6 illustrates the MSE performance versus SNR for different batch sizes during training. The larger the batch size, the more SNR the higher, the more accurate the estimation.The higher SNR the more accurate the estimation, as it is seen as SNR increases from 5dB to 30dB, the MSE decreased consistently for all batch sizes. At higher SNR, smaller batch sizes (e.g., 10, 20) quickly converge towards larger batch sizes, and the MSE is initially high for small batch sizes. As can be seen, batch size 50 performs well at all SNR values, and batch size 100 performs competitively with regard to accuracy, especially at low-to-mid SNR values.

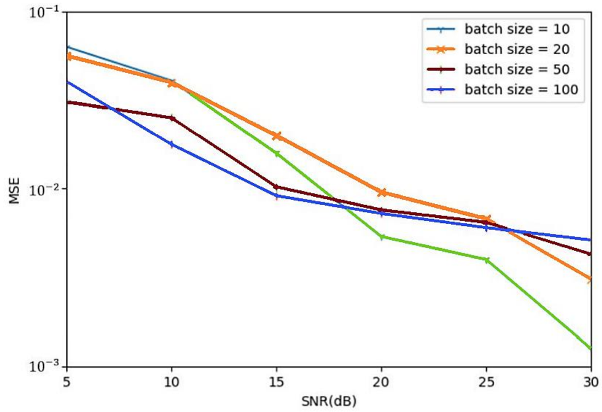

Figure 6 Comparison of MSE vs SNR

5. CONCLUSION

In this research a novel Spiking Neural Network-Based NOMA-OFDM Processing Under Weibull Fading for Accurate Uplink Signal Prediction has been proposed. During the offline stage, these labeled NOMA-OFDM signals should be fed into a Weibull fading channel for the generation of training data and labels, and then the trained SNN is used to predict the signals accurately. During the online stage, the fading channels effect of real-time NOMA-OFDM signals is the same as the offline stage, and the processed signals are used to predict the fading channels effects without the need for label information with the trained SNN. Such an approach helps achieve strong channel estimation and signal detection, taking advantage of the flexibility and learning ability of the SNN. Future research under single input, multi output (SIMO) or multi input, single output (MISO) with various modulation schemes and fading channel types might further investigate the performance of the suggested model.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

FUNDING STATEMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to the supervisor and faculty members for their valuable guidance and continuous support throughout this research work.

REFERENCES

1 Rehman, S.U., Ahmad, J., Manzar, A. and Moinuddin, M., 2024. Beamforming techniques for mimo-noma for 5g and beyond 5g: Research gaps and future directions. Circuits, Systems, and Signal Processing, 43(3), pp.1518-1548. [CrossRef] [Google Scholar] [Publisher Link]

2. Nanda, S., Alayu, M., Swayamsiddha, S., Ray, K., Sahoo, S. and Das, L., 2024. Signal Processing based Iterative Channel Estimation Techniques for Noma-OFDM Systems. Journal of Engineering Science & Technology Review, 17(5). [CrossRef] [Google Scholar] [Publisher Link]
3. Jha, S.K., Kumar, N. and Kumar, P., 2025. A ZCZ-based NOMA-CDMA system for enhanced user scalability under similar channel conditions. Physical Communication, p.102740. [CrossRef] [Google Scholar] [Publisher Link]
4. Manogaran, N. and Palanivel, M., 2024. Performance analysis of non-linear constellation precoded NOMA over Rayleigh fading channel. Results in Engineering, 24, p.103522. [CrossRef] [Google Scholar] [Publisher Link]
5. Kieu-Xuan, T. and Le-Thi, A., 2024. UAV-Assisted Cooperative NOMA and OFDM Communication Systems: Analysis and Optimization. Journal of Sensor and Actuator Networks, 13(1), p.18. [CrossRef] [Google Scholar] [Publisher Link]
6. Dai, L., Wang, B., Yuan, Y., Han, S., Chih-Lin, I. and Wang, Z., 2015. Non-orthogonal multiple access for 5G: solutions, challenges, opportunities, and future research trends. IEEE Communications Magazine, 53(9), pp.74-81. [CrossRef] [Google Scholar] [Publisher Link]
7. Liu, Y., Ouyang, C., Ding, Z. and Schober, R., 2024. The road to next-generation multiple access: A 50-year tutorial review. Proceedings of the IEEE. [CrossRef] [Google Scholar] [Publisher Link]
8. Yu, D., Wu, Z., Zhang, H., Li, H. and Fu, S., 2024. Deep Learning for Signal Detection in Non-orthogonal Multiple Access Orthogonal Time-Frequency Space. [CrossRef] [Google Scholar] [Publisher Link]
9. Panda, B. and Singh, P., 2024. Deep learning-based sequential models for multi-user detection with M-PSK for downlink NOMA wireless communication systems. Annals of Telecommunications, 79(5), pp.327-341. [CrossRef] [Google Scholar] [Publisher Link]
10. Elmahallawy, M., Luo, T. and Ramadan, K., 2024. Communication-efficient federated learning for LEO constellations integrated with HAPs using hybrid NOMA-OFDM. IEEE Journal on Selected Areas in Communications, 42(5), pp.1097-1114. [CrossRef] [Google Scholar] [Publisher Link]
11. VK, J., 2024. Co-operative non-orthogonal multiple access networks: a survey. World Journal of Engineering, 21(6), pp.1128-1141. [CrossRef] [Google Scholar] [Publisher Link]
12. Rehman, S.U., Ahmad, J., Manzar, A. and Moinuddin, M., 2024. Beamforming techniques for mimo-noma for 5g and beyond 5g: Research gaps and future directions. Circuits, Systems, and Signal Processing, 43(3), pp.1518-1548. [CrossRef] [Google Scholar] [Publisher Link]
13. Nanda, S., Alayu, M., Swayamsiddha, S., Ray, K., Sahoo, S. and Das, L., 2024. Signal Processing based Iterative Channel Estimation Techniques for Noma-OFDM Systems. Journal of Engineering Science & Technology Review, 17(5). [CrossRef] [Google Scholar] [Publisher Link]
14. Rahman, M.H., Sejan, M.A.S., Yoo, S.G., Kim, M.A., You, Y.H. and Song, H.K., 2022. Multi-user joint detection using bi-directional deep neural network framework in NOMA-OFDM system. Sensors, 22(18), p.6994. [CrossRef] [Google Scholar] [Publisher Link]
15. Gaballa, M., Abbod, M. and Aldallal, A., 2022. Investigating the combination of deep learning for channel estimation and power optimization in a non-orthogonal multiple access system. Sensors, 22(10), p.3666[CrossRef] [Google Scholar] [Publisher Link]
16. Panda, B. and Singh, P., 2023. A deep convolutional-LSTM neural network for signal detection of downlink NOMA system. AEU-International Journal of Electronics and Communications, 170, p.154797. [CrossRef] [Google Scholar] [Publisher Link]
17. Xie, Y., Teh, K.C. and Kot, A.C., 2021. Deep learning-based joint detection for OFDM-NOMA scheme. IEEE Communications Letters, 25(8), pp.2609-2613. [CrossRef] [Google Scholar] [Publisher Link]
18. Pandya, S., Wakchaure, M.A., Shankar, R. and Annam, J.R., 2022. Analysis of NOMA-OFDM 5G wireless system using deep neural network. The Journal of Defense Modeling and Simulation, 19(4), pp.799-806. [CrossRef] [Google Scholar] [Publisher Link]
19. Chuan, L.I.N., Qing, C. and Xianxu, L.I., 2020. Uplink NOMA signal transmission with convolutional neural networks approach. Journal of Systems Engineering and Electronics, 31(5), pp.890-898. [CrossRef] [Google Scholar] [Publisher Link]
20. Sim, I., Sun, Y.G., Lee, D., Kim, S.H., Lee, J., Kim, J.H., Shin, Y. and Kim, J.Y., 2020. Deep learning based successive interference cancellation scheme in nonorthogonal multiple access downlink network. Energies, 13(23), p.6237. [CrossRef] [Google Scholar] [Publisher Link]

AUTHORS

M. Sandhya Magesh is working as a Professor in School of Computer Science & Engineering in Vellore Institute of Technology, Chennai Campus. With over twenty-five years of experience, she has published around 75 papers in reputed International Conferences and journals like IEEE Access, Wireless Personal Communications, Arabian Journal of Science and Engineering, etc. She is a powerful force in the workplace and uses her positive attitude and tireless energy to encourage others to work hard and succeed. Her research interests include Health Care Applications, Wireless Security, RFID, Data Analytics.

W. Aisha Banu Wahab is a Professor and Head of the Department of Computer Science and Engineering at B. S. Abdur Rahman Crescent Institute of Science and Technology. She has been serving in the institute since 1997, with over two decades of academic and research experience. She holds a Ph.D. in Computer Science and Engineering from Anna University, Chennai. Her areas of expertise include Cloud Computing, Social Network Analysis, Information Retrieval, and Big Data. She has published more than 68 research papers in reputed journals and international conferences. She has successfully guided 6 Ph.D. scholars in various domains of Computer Science. Dr. Aisha Banu has been involved in multiple funded consultancy and research projects. She has organized and participated in numerous FDPs, workshops, and national conferences. She has served in key administrative roles such as NBA Coordinator, Research Supervisor, and ISO Auditor. She is also a member of the Board of Studies and Academic Council at the institute.

Arputha Rathina Xavier is currently Associate Professor in the Department of Computer Science and Engineering, B.S.Abdur Rahman University. She has been working in this Institution for the past 25 years. Her area of interest includes Image Processing, Human Computer Interaction and Emotional Intelligence. She has guided more than 40 UG and 25 PG projects. She has visited Hiroshima University - Japan, to acquire the basic knowledge on Kansei Engineering. She did her thesis in the area of Emotion detection using Facial expressions and Speech. She is a member of ACM and IEEE.

Arrived: 05. 03. 2026

Accepted: 10. 04. 2026