International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 2, April 2024, pp. 2035∼2042
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i2.pp2035-2042

An efficient convolutional neural network-extreme gradient boosting hybrid deep learning model for disease detection applications

Navaneeth Bhaskar[1], Aswathy Maruthompilli Ajithkumar[2], Priyanka Tupe-Waghmare[3]
[1]Department of Computer Science and Engineering (Data Science), Sahyadri College of Engineering and Management, Mangalore, India
[2]School of Electronics and Telecommunication Engineering, MIT Academy of Engineering, Alandi, Pune, India
[3]Symbiosis Institute of Technology, Symbiosis International (Deemed University), Pune, India

Article Info

Article history:

Received Jul 30, 2023
Revised Sep 23, 2023
Accepted Oct 9, 2023

Keywords:

Convolutional neural network
Deep learning
Extreme gradient boosting
Gas sensor
Signal processing
Type-2 diabetes

ABSTRACT

In this paper, we present an efficient deep-learning hybrid model comprising an extreme gradient boosting (XGBoost) supervised learning algorithm and convolutional neural networks (CNN) for the automated detection of diseases. The proposed model is implemented and tested to detect type-2 diabetes by measuring the acetone concentration in the exhaled breath. Acetone will be present in much higher concentrations in type-2 diabetic patients compared to non-diabetic people. A novel sensing module is designed and implemented in our study to measure the acetone concentration in exhaled breath. The proposed approach delivered good results, with a classification accuracy of 97.14%. The findings of this study show how effectively the proposed detection module functions in disease diagnosis applications. As the detection process is simple and non-invasive, people can undergo routine checks for diabetes with the proposed detection module.

Corresponding Author:

Aswathy Maruthompilli Ajithkumar
School of Electronics and Telecommunication Engineering, MIT Academy of Engineering
Alandi, Pune, India
Email: aswathy.ma@mitaoe.ac.in

1. INTRODUCTION

Machine learning models are commonly used to analyze medical signals to detect disease automatically. Since feature extraction and classification tasks are carried out using two different procedures, traditional machine learning algorithms are unable to produce more reliable results in medical diagnostic applications. In recent years, convolutional neural networks (CNN) have largely replaced conventional machine learning techniques in medical diagnosis [1], [2]. The CNN itself executes both the feature extraction and the classification tasks in the CNN learning network. As a result, a separate feature extraction module is no longer necessary. For automated disease identification, CNN offers more reliable results as compared to conventional learning models. The development of CNN models has been greatly influenced by the application of novel architectural principles and parameter optimization strategies [3]. The CNN models have advanced significantly during the last few years. The fundamental issue that researchers run into when developing new CNN models is the gradient descent problem. The design issues were resolved by implementing cross-layer channel connections, skipping connections and multiple-layer attachments. Researchers have suggested hybrid networks, which incorporate several learning models, to improve classification performance [4].

In this paper, we have designed and implemented an efficient convolutional neural network-extreme gradient boosting (CNN-XGBoost) hybrid model that can automatically predict disease without the help of medical experts. A novel sensing model that can identify diabetes from exhaled breath has been developed to test and validate the proposed deep-learning model. One of the most effective non-invasive techniques for disease identification is breath-based screening. Due to its advantages over conventional invasive approaches, non-invasive disease detection techniques have been increasingly popular in recent years [5]. These methods eliminate the need for intrusive sampling or surgical procedures in the detection, diagnosis and monitoring of diseases. Exhaled breath has a lot of potential for clinical diagnostics, and it is possible that in the not-too-distant future, it might end up becoming the most trustworthy and popular diagnostic tool for non-invasively diagnosing many diseases. Exhaled breath contains a large number of biomarkers, according to medical researchers [6]. numerous volatile organic compounds (VOCs) found in the breath can act as markers for different physiological and pathological situations in the body. Analyzing a person's breath composition can provide important details about their health. VOCs are small compounds that are exhaled as byproducts of metabolism or as a result of some disease processes. Since various medical conditions are connected to unique VOC patterns, it is possible to identify many diseases by analyzing the concentrations of VOCs. Acetone, Isoprene, ethanol, methanol and other alcohols are the main VOCs found in healthy people's exhaled breath [7]. Table 1 displays the main VOCs and their concentrations in a healthy person. The concentration values are expressed in parts per billion (ppb). Increased levels of these VOCs are indicative of systemic diseases and organ failures. High amounts of blood-derived biomarkers passively migrate through the lung's alveolar membrane and into a person's breath. Breath-based testing allows for the investigation of many medical conditions.

Table 1. VOCs and their concentrations in exhaled breath

VOCs in Breath	Concentration Range (ppb)	References
Acetone	656–836	[8]
Isoprene	70–580	[9]
Methanol	400–2000	[7]
Ethanol	37–207	[7]
Isopropanol	50–260	[9]
Butanone	6–26	[9]
Acetaldehyde	3–7	[10]

Blood glucose testing is the standard and medically recognized procedure for detecting diabetes. During the diabetes blood test, the patient's blood glucose level is assessed after an overnight fast. When the blood glucose reading of 126 mg/dL or higher is obtained, diabetes is considered to be present [8]. Blood-based diagnosis has several limitations because it is an intrusive procedure. Additionally, if the approach is intrusive, routine testing is impossible. Early detection and diagnosis of diabetes are necessary to enable rapid management and intervention to avoid complications. For people with diabetes to maintain a good and healthy life, regular blood glucose testing and continued medical care are essential. Monitoring acetone levels in breath is a promising approach for diabetes detection and management. Acetone is one of the VOCs present in breath, and its levels can be indicative of metabolic changes related to diabetes. Diabetes may cause insulin deficit or resistance, which causes the body to break down fat for energy more often. Acetone is one of the ketone bodies that are produced as a consequence of this activity. The generated acetone is expelled through the exhaled breath. According to studies, type-2 diabetic patients have been reported to have higher breath acetone levels [10]. Monitoring the concentrations of this ketone in exhaled breath can therefore be used to identify diabetes. Very little acetone gas concentration is present in the exhaled breath. As a result, detection is challenging and requires extremely sensitive sensors to determine the levels of breath acetone. There are not many devices available for determining the level of acetone in breath. Metal oxide semiconductor (MOS) sensors are the best sensors for monitoring gas concentrations [11]. Therefore, in the proposed work, we developed a MOS sensor-based detection apparatus to measure acetone concentration in the exhaled breath.

2. ARCHITECTURE OF THE PROPOSED HYBRID MODEL

We have developed a CNN-XGBoost deep learning hybrid model that combines CNN with XGBoost, an implementation of the gradient boosting method, to classify the breath samples to make predictions. This hybrid model's prediction performance and accuracy are increased since it combines the benefits of CNN and

XGBoost [12].

2.1. Module for extracting features

Deep-learning models such as CNNs are frequently utilized for image and pattern recognition applications. They are made up of several layers, including fully connected, pooling and convolutional layers. CNNs can be used for extracting features because they can automatically learn hierarchical representations of features from the input data [13]. The first layer in the CNN module is the convolution layer. The sensor's output signal is directly provided to the CNN as an input. Since the input of our model is a one-dimensional (1-D) signal, we have designed and applied a 1-D CNN model. Through the use of kernels, this layer extracts the various input features. A two-function mathematical operation is used in the convolution process. It produces a result that consists of multiplying one function and creating a shifted and reversed counterpart of the other function. The convolution layer serves as the foundation of the CNN structure [14]. The 1-D CNN's forward propagation is performed as (1):

$$y_l^k = b_l^k + \sum_{i=1}^{N_{k-1}} Conv(w_{il}^{k-1}, s_i^{k-1}) \tag{1}$$

where y_l^k represents the input feature, b_l^k denotes the bias of the l^{th} neuron, w_{il}^{k-1} denotes the kernel from i^{th} neuron, and s_i^{k-1} represents the output of the i^{th} neuron.

From the output layer's fully connected output, the error starts to back propagate. The mean square error (MSE) for the output layer, or K layer, for the input vector q is represented as (1):

$$E_r = MSE[t_i^q(x_1^K, ..., x_{N_K}^K)] = \sum_{i=1}^{N_K}(x_i^K - t_i)^2 \tag{2}$$

Here, E_r is the MSE, N_K is the number of classes, t_i^q is the target vector and $(x_1^K, ..., x_{N_K}^K)$ is the output vector.

Once the error has been determined, the gradient descent method can be used to update the relevant weights and biases [15]. By estimating its sensitivity by learning factor γ, the weights and biases are updated as (3) and (4):

$$w_{il}^{k-1}(t+1) = w_{il}^{k-1}(t) - \gamma \frac{\partial E}{\partial w_{il}^{k-1}} \tag{3}$$

$$b_l^k(t+1) = b_l^k(t) - \gamma \frac{\partial E}{\partial b_l^k} \tag{4}$$

The multilayer perceptron (MLP) layer handles classification in conventional CNN [16]. By combining a more powerful classification method, the CNN model's performance can be improved. Recent research has shown that integrating CNN models with a better classifier, such as support vector machine (SVM), can enhance classification performance. In many research studies, integrated CNN-SVM models are used for various applications [17].

2.2. Sample classification module

For the XGBoost to do the classification task, the features extracted by CNN are given as input. The gradient boosting framework is implemented in XGBoost, which creates an ensemble of weak prediction models successively, with each model fixing the flaws of the preceding models [18]. Decision trees serve as the foundational learners in XGBoost, while it can also operate with other weak learner types. It greedily builds shallow trees while continuously improving a user-defined objective function.

For the dataset with n features and m examples can be represented as $D = (y_i, x_i)(D = n, y_i R^m, x_i \in R)$. Here y and x represent the eigenvalue and true value, respectively. The output of the bosting model with l trees is expressed as (5):

$$x_i' = \sum_{l=1}^{l} f_l(y_i), f_l \in S \tag{5}$$

where space for classification $\{S = f(x) = w_p(x)\}(p : R^m \to F, w \in R^F)$. Here $w_p(x)$ corresponds to the weight of the leaf nodes and $f(x)$ represents the trees. Each tree's structure, represented by p, and the number of leaf nodes, represented by F, are what correlate to the sample's matching leaf node.

Since the model's objective is to learn these k trees, the following objective function is minimized:

$$T^{(t)} = \sum_{l=1}^{n} k(x_i, x_i') + \sum_{l=1}^{L} \Omega(f_l) \tag{6}$$

where the loss function k represents the discrepancy between the estimated and true values. Ω corresponds to the regularization parameter.

Regularization techniques are used in XGBoost to reduce overfitting and boost generalization. The extracted features are fed into an XGBoost classifier during training. Based on the CNN-generated feature representations, XGBoost will learn to predict outcomes. To enhance the performance of the model, the weak models are combined using gradient boosting [19].

3. MODULE AND TESTING FOR DIABETES DETECTION

We have developed a test chamber in order to carry out the testing procedure. The process control flow of the whole system is illustrated in Figure 1. MOS sensors are useful for detecting trace levels of chemicals in breath samples since they can detect low concentrations of gases. In this study, we employed a TGS 1820 acetone gas sensor for detection. This sensor's ability to detect acetone concentrations allows for a higher level of analysis selectivity. The sensing element consists of a noble metal coil embedded in a small bead of sintered metal oxide semiconductor material. MOS sensors enable the detection module to be portable, user-friendly and deployable in a variety of scenarios, including point-of-care applications. The oxidation-reduction events that happen between the gas molecules and the surface of the semiconductor serve as the foundation for the sensing mechanism in MOS gas sensors. The conductivity of the TGS 1820 sensor changes as acetone in the gas chamber interacts with the detecting component. To calculate the gas concentration, the electrical resistance caused by a change in the semiconductor material's conductivity is measured [20].

As the sensor interacts with the acetone gas in the gas chamber, the charge distribution in the semiconductor material changes. The conductivity modulation causes a change in the output current that flows through the sensor. The output current is calculated and analyzed to detect the presence of acetone gas. This is done with the help of an electrical circuit. The sensors fundamental measurement circuit is a Wheatstone bridge circuitry. The four arms of the bridge, which include the sensor heater, the load resistor for the output, and two opposite side resistors for the reference voltage, are subjected to a circuit voltage of 2.30±0.05 V. The difference between the reference voltage and the divided voltage is used to calculate the sensor output voltage. Using a DHT11 sensor, temperature and humidity inside the chamber are measured [21]. Both temperature and humidity are measured and analyzed to ensure a regulated and ideal environment for testing,

There is a mouthpiece for blowing exhaled breath in the front of the gas chamber. The TGS 1820 and DHT11 sensors are connected inside the gas chamber. The graphical model of the designed gas chamber is shown in Figure 2. The signal variations are collected for 100 seconds to analyze and categorize the signal values obtained from the sensors. Tests were conducted using the proposed sensing module on 112 non-diabetic people and 98 diabetic patients with type 2 diabetes to evaluate the proposed model. The basic testing protocols were followed before the testing phase, and the experimentation was carried out by following the Declaration of Helsinki regulations. Prior to the analysis, oral health advice was given to all participants. Figure 3 shows the voltage output signal of the sensor for a diabetic and non-diabetic test sample. The analog signals are acquired using an Arduino board with an ATmega328P controller. The Arduino board is interfaced and communicated using MATLAB support packages for Arduino hardware.

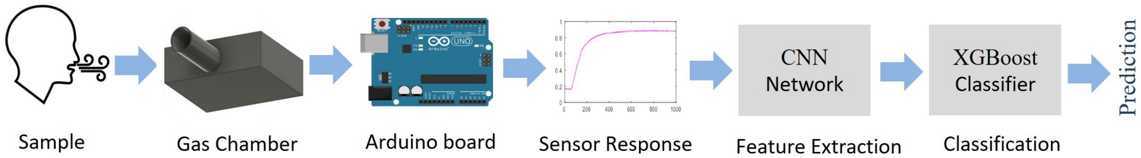

Figure 1. Block diagram of the overall system illustrating the process control flow

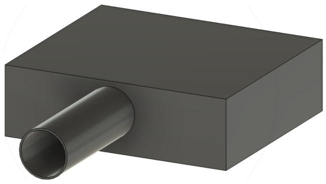

Figure 2. An illustration of the designed gas chamber. The sensors are mounted within the gas chamber

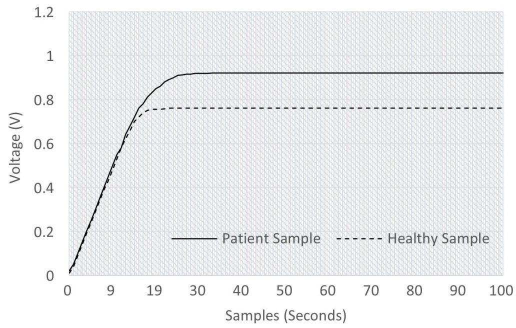

Figure 3. Voltage output signals from the sensor module for a diabetic and non-diabetic test sample

4. RESULTS AND DISCUSSION

This study set out to create an automated method of detecting diabetes by analyzing exhaled breath. This work uses machine learning techniques to generate automatic predictions for the tested samples. The sensor output signal is fed into the learning models, which then automatically analyze and predict the output. The best and the most accurate method to diagnose diabetes is by measuring blood glucose levels. In contrast, we are identifying diabetes from the exhaled breath sample, to make the process non-invasive. Since breath-based analysis is not used in medical diagnosis, we have done an investigation to examine the feasibility of using breath acetone to detect type-2 diabetes. To determine the relationship between blood glucose levels and the level of breath acetone in both diabetic patients and non-diabetic people, we used Pearson's correlation analysis [22]. The correlation coefficient from Pearson's analysis is used to determine how closely these two variables are related. While blood glucose levels are assessed using the conventional clinical analysis approach, the proposed sensing module is used to quantify the acetone concentration in the breath. The values for breath acetone and blood glucose were correlated with each other in our studies with a 0.916 correlation coefficient. A strong positive correlation between these two variables is indicated by the high correlation value. It is abundantly evident from this that as blood glucose levels rise in diabetic patients, their breath acetone levels would increase.

The best features are extracted from the sensor signal by the CNN model. The integrated XGBoost classifier is then used to classify the test samples based on these features. A k-fold validation technique is used for validation. We have developed and evaluated traditional machine learning models and hybrid models with the same test samples to compare the performance. The traditional network algorithms used for comparison include CNN-SVM, CNN-MLP, SVM classifiers with singular value decomposition (SVD), K-nearest neighbours (KNN) algorithm with principal component analysis (PCA) feature extraction, recurrent neural network (RNN), long short-term memory (LSTM), and CNN-RF combined network [23]–[25]. The proposed deep-learning network is built using CNN and the XGBoost classifier. For examining the effectiveness of each of these models, a detailed performance comparison was carried out. Table 2 displays the performance values obtained for each of these approaches. Features are extracted using the PCA and SVD algorithms, and the features are then classified using the SVM and KNN algorithms. The K in KNN denotes the number of nearest neighbours to take into account when making a prediction [26]. The goal of SVM is to define the hyperplane that maximises the margin between the healthy and diabetic patient classes. The SVM classifier predicts the class label of new, unseen data points based on which side of the hyperplane they fall on after determining the ideal hyperplane during the training phase. The accuracy of the sample identification by the SVD-SVM and PCA-KNN algorithms was 87.14% and 85.71%, respectively.

Table 2. Comparison of performance metrics obtained for the proposed model and other models compared in this study

Models	Accuracy (%)	Sensitivity	Specificity	Precision	F1 Score	Error Rate
SVD-SVM	87.14	0.891	0.857	0.826	0.857	0.128
PCA-KNN	85.71	0.869	0.847	0.816	0.842	0.143
RNN	90.48	0.924	0.889	0.867	0.895	0.095
LSTM	91.9	0.945	0.899	0.878	0.91	0.081
CNN-RF	95.24	0.989	0.925	0.908	0.945	0.047
CNN-MLP	95.71	0.989	0.932	0.918	0.952	0.043
CNN-SVM	96.19	0.979	0.948	0.939	0.958	0.038
CNN-XGBoost	97.14	0.979	0.965	0.959	0.969	0.028

The essential notion behind RNN is to use the outcome of the previous time step as input for the current time step, effectively generating a temporal chain or sequence of computations. LSTM is a form of RNN developed to address the issues of vanishing and bursting gradients and more efficiently capture long-term dependencies. Traditional machine learning methods are outperformed by the CNN-based network because it can identify the most effective features from the sensor response. The accuracy attained by CNN-RF combined network is 95.24%. When the MLP layer was switched out for an SVM classifier, CNN's prediction accuracy increased. The CNN-MLP and CNN-SVM classifiers are found to be 95.71% and 96.19% accurate, respectively, at predicting diabetes with the proposed sensing model. The proposed CNN-XGBoost network has the highest accuracy of 97.14% when measured against the other algorithms looked at in the present study. This network has an error rate of 0.028, which is quite low when compared to all other techniques. The proposed approach correctly classified 110 samples as healthy and 94 samples as diabetes patients out of the 210 samples tested. Only six samples were misclassified by this model.

To provide a graphical representation of the relationship between sensitivity and specificity for different cut-off values for the tests, Receiver Operating Characteristic (ROC) curves are plotted for the proposed model and CNN-SVM model. The ROC performance indicates how effectively breath acetone can identify a person as a diabetic patient or not. The ROC plot is a graphical representation of sensitivity versus 1-specificity for different test set cut-off values [27]. Figure 4 displays the ROC plot for the CNN-SVM and CNN-XGBoost models. The Area Under the Curve (AUC) is calculated from this plot to verify the accuracy of the analysis. For the CNN-XGBoost and CNN-SVM classification models, the AUC values obtained are 0.968 and 0.959, respectively. This makes it very evident how much superior the proposed model is to the CNN-SVM hybrid model.

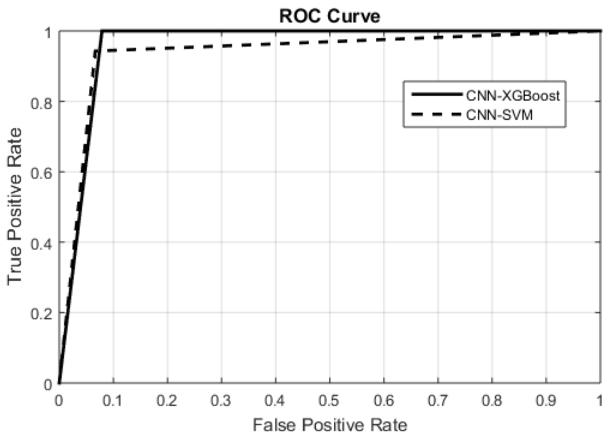

Figure 4. ROC curves for CNN-XGBoost and CNN-SVM classifier models that were obtained for testing samples

5. CONCLUSION

In this study, the CNN model and the XGBoost classifier were combined to build a hybrid deep-learning model for medical diagnosis applications. The benefits of XGBoost and CNNs can be combined to improve performance using an ensemble technique. A strong hybrid model can be created by using CNNs to extract features from sensor responses and then combining those features with tabular data for XGBoost training. The deep learning model is applied to identify type-2 diabetes based on quantitative measurements of acetone gas concentrations observed in breath signals. A novel sensor module is developed and deployed in this study to measure and quantify the acetone concentration in exhaled breath. If the sensor is operated outside of its normal operating conditions, we must account for humidity variations. The effect of humidity can be compensated by employing humidity sensors and correcting the sensor response accordingly. Analysis metrics were compared with traditional machine learning models to validate the performance of the system. The best accuracy was achieved by the proposed CNN-XGBoost classifier, which was 97.14%. ROC analysis and correlation analysis are carried out to validate the methodology and apparatus used in this research. The proposed hybrid model effectively reduces the complexity involved in using two different models for feature extraction and classification. The proposed method for breath analysis eliminates the need for blood sampling or other invasive procedures. Patients are more likely to accept this detection technique because it is simple and non-invasive, potentially leading to more regular testing.

REFERENCES

[1] Z. Wu *et al.*, "Studies on different CNN algorithms for face skin disease classification based on clinical images," *IEEE Access*, vol. 7, pp. 66505–66511, 2019, doi: 10.1109/ACCESS.2019.2918221.

[2] B. Navaneeth and M. Suchetha, "PSO optimized 1-D CNN-SVM architecture for real-time detection and classification applications," *Computers in Biology and Medicine*, vol. 108, pp. 85–92, May 2019, doi: 10.1016/j.compbiomed.2019.03.017.

[3] W. Wang, R. Yang, C. Guo, and H. Qin, "CNN-based hybrid optimization for anomaly detection of rudder system," *IEEE Access*, vol. 9, pp. 121845–121858, 2021, doi: 10.1109/ACCESS.2021.3109630.

[4] A. M. Roy and J. Bhaduri, "DenseSPH-YOLOv5: An automated damage detection model based on DenseNet and swin-transformer prediction head-enabled YOLOv5 with attention mechanism," *Advanced Engineering Informatics*, vol. 56, Apr. 2023, doi: 10.1016/j.aei.2023.102007.

[5] Y. L. Pham and J. Beauchamp, "Breath biomarkers in diagnostic applications," *Molecules*, vol. 26, no. 18, Sep. 2021, doi: 10.3390/molecules26185514.

[6] G. B. Hanna, P. R. Boshier, S. R. Markar, and A. Romano, "Accuracy and methodologic challenges of volatile organic compound-based exhaled breath tests for cancer diagnosis: a systematic review and meta-analysis," *JAMA oncology*, vol. 5, no. 1, pp. e182815–e18281, 2019.

[7] J. D. Fenske and S. E. Paulson, "Human breath emissions of VOCs," *Journal of the Air and Waste Management Association*, vol. 49, no. 5, pp. 594–598, May 1999, doi: 10.1080/10473289.1999.10463831.

[8] S. Lekha and S. M, "Recent advancements and future prospects on e-nose sensors technology and machine learning approaches for non-invasive diabetes diagnosis: A review," *IEEE Reviews in Biomedical Engineering*, vol. 14, pp. 127–138, 2021, doi: 10.1109/RBME.2020.2993591.

[9] A. Hansel, A. Jordan, R. Holzinger, P. Prazeller, W. Vogel, and W. Lindinger, "Proton transfer reaction mass spectrometry: on-line trace gas analysis at the ppb level," *International Journal of Mass Spectrometry and Ion Processes*, vol. 149–150, pp. 609–619, Nov. 1995, doi: 10.1016/0168-1176(95)04294-U.

[10] Y. Lin, S. R. Dueker, A. D. Jones, S. E. Ebeler, and A. J. Clifford, "Protocol for collection and HPLC analysis of volatile carbonyl compounds in breath," *Clinical Chemistry*, vol. 41, no. 7, pp. 1028–1032, Jul. 1995, doi: 10.1093/clinchem/41.7.1028.

[11] M. Gancarz, A. Nawrocka, and R. Rusinek, "Identification of volatile organic compounds and their concentrations using a novel method analysis of MOS sensors signal," *Journal of Food Science*, vol. 84, no. 8, pp. 2077–2085, Aug. 2019, doi: 10.1111/1750-3841.14701.

[12] D. Zhang, L. Qian, B. Mao, C. Huang, B. Huang, and Y. Si, "A data-driven design for fault detection of wind turbines using random forests and XGboost," *IEEE Access*, vol. 6, pp. 21020–21031, 2018, doi: 10.1109/ACCESS.2018.2818678.

[13] N. Bhaskar and M. Suchetha, "An approach for analysis and prediction of CKD using deep learning architecture," in *2019 International Conference on Communication and Electronics Systems (ICCES)*, Jul. 2019, pp. 1660–1664, doi: 10.1109/ICCES45898.2019.9002214.

[14] A. Singh, K. Raj, T. Kumar, S. Verma, and A. M. Roy, "Deep learning-based cost-effective and responsive robot for autism treatment," *Drones*, vol. 7, no. 2, Jan. 2023, doi: 10.3390/drones7020081.

[15] S. Rehman, S. Tu, O. Rehman, Y. Huang, C. Magurawalage, and C.-C. Chang, "Optimization of CNN through novel training strategy for visual classification problems," *Entropy*, vol. 20, no. 4, Apr. 2018, doi: 10.3390/e20040290.

[16] M. Desai and M. Shah, "An anatomization on breast cancer detection and diagnosis employing multi-layer perceptron neural network (MLP) and convolutional neural network (CNN)," *Clinical eHealth*, vol. 4, pp. 1–11, 2021, doi:

10.1016/j.ceh.2020.11.002.
[17] N. Bhaskar, V. Bairagi, E. Boonchieng, and M. V Munot, "Automated detection of diabetes from exhaled human breath using deep hybrid architecture," *IEEE Access*, vol. 11, pp. 51712–51722, 2023, doi: 10.1109/ACCESS.2023.3278278.
[18] Y. Jiang, G. Tong, H. Yin, and N. Xiong, "A pedestrian detection method based on genetic algorithm for optimize XGBoost training parameters," *IEEE Access*, vol. 7, pp. 118310–118321, 2019, doi: 10.1109/ACCESS.2019.2936454.
[19] H. Li, B. Pu, Y. Kang, and C. Y. Lu, "Research on massive ECG data in XGBoost," *Journal of Intelligent and Fuzzy Systems*, vol. 36, no. 2, pp. 1161–1169, Mar. 2019, doi: 10.3233/JIFS-169890.
[20] C. Krutzler, A. Unger, H. Marhold, T. Fricke, T. Conrad, and A. Schütze, "Influence of MOS gas-sensor production tolerances on pattern recognition techniques in electronic noses," *IEEE Transactions on Instrumentation and Measurement*, vol. 61, no. 1, pp. 276–283, Jan. 2012, doi: 10.1109/TIM.2011.2161015.
[21] G. M. Debele and X. Qian, "Automatic room temperature control system using Arduino UNO R3 and DHT11 sensor," in *2020 17th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP)*, Dec. 2020, pp. 428–432, doi: 10.1109/ICCWAMTIP51612.2020.9317307.
[22] P. Ahlgren, B. Jarneving, and R. Rousseau, "Requirements for a cocitation similarity measure, with special reference to Pearson's correlation coefficient," *Journal of the American Society for Information Science and Technology*, vol. 54, no. 6, pp. 550–560, Apr. 2003, doi: 10.1002/asi.10242.
[23] J. Wang, Y. Sun, and S. Sun, "Recognition of muscle fatigue status based on improved wavelet threshold and CNN-SVM," *IEEE Access*, vol. 8, pp. 207914–207922, 2020, doi: 10.1109/ACCESS.2020.3038422.
[24] S. Wang, R. Yao, T. A. Tsiftsis, N. I. Miridakis, and N. Qi, "Signal detection in uplink time-varying OFDM systems using RNN with bidirectional LSTM," *IEEE Wireless Communications Letters*, vol. 9, no. 11, pp. 1947–1951, Nov. 2020, doi: 10.1109/LWC.2020.3009170.
[25] P. Tupe-Waghmare *et al.*, "Comprehensive genomic subtyping of glioma using semi-supervised multi-task deep learning on multimodal MRI," *IEEE Access*, vol. 9, pp. 167900–167910, 2021.
[26] M. Bansal, A. Goyal, and A. Choudhary, "A comparative analysis of K-nearest neighbor, genetic, support vector machine, decision tree, and long short term memory algorithms in machine learning," *Decision Analytics Journal*, vol. 3, Jun. 2022, doi: 10.1016/j.dajour.2022.100071.
[27] R. C. Prati, G. E. A. P. A. Batista, and M. C. Monard, "Evaluating classifiers using ROC curves," *IEEE Latin America Transactions*, vol. 6, no. 2, pp. 215–222, Jun. 2008, doi: 10.1109/TLA.2008.4609920.

BIOGRAPHIES OF AUTHORS

Navaneeth Bhaskar received the B.E. and M.Tech. degree in electronics from Visvesvaraya Technological University, and Ph.D degree in machine learning from VIT University, India. Currently, he is working as associate professor in the Department of Computer Science and Engineering (data acience) at Sahyadri College of Engineering and Management, India. His research interests include artificial intelligence, machine learning, data analytics, IoT and signal processing. He is a life member of the Data Science Association and the International Association of Engineers. He can be contacted at email: navbskr@gmail.com.

Aswathy Maruthompilli Ajithkumar is working as an assistant professor with the School of Electronics and Telecommunication Engineering, Pune, India. She is pursuing her Ph.D degree at Vellore Institute of Technology, Chennai, India. She has received her B.Tech degree in electronics and communication engineering and M.E. degree in applied electronics. Her fields of interest are biomedical engineering, health care, computer vision and data science. She can be contacted at email: aswathy.ma@mitaoe.ac.in.

Priyanka Tupe-Waghmare completed her Ph.D. in engineering from Symbiosis International (Deemed University). She has been working as assistant professor at Symbiosis Institute of Technology, Pune since 2011. Her area of expertise lies in medical image analysis and applied artificial intelligence. She is a senior member of IEEE, and associate member of the Institution of Engineers (India) and the International Society for Magnetic Resonance in Medicine. She was a recipient of the prestigious ISMRM Magna Cumlaude Merit Award for presenting her work at ISMRM and SMRT Annual Meeting and Exhibition in 2021. She can be contacted at email: priyanka.tupe@sitpune.edu.in.