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Robust Classification of Traffic Signs Using Relief Feature Reduction Technique

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Abstract

Ensuring driver safety amidst the rapid growth of global population and vehicular density continues to be a paramount challenge for transportation authorities and governments worldwide. With the rise of smart mobility solutions and autonomous driving technologies, the ability to detect, classify, and respond to traffic signs accurately has become critically important, especially under diverse and adverse environmental conditions such as rain, fog, or poor lighting. Reliable traffic sign recognition not only ensures the safety of autonomous vehicle passengers but also contributes significantly to real-time decision-making on the road. Previous studies have explored a wide range of Artificial Intelligence (AI) and machine learning techniques for traffic sign detection and classification. However, many approaches face challenges related to feature redundancy and model generalization across complex datasets. This study addresses these limitations by leveraging the publicly available Mapillary traffic sign image dataset and applying the RRelieff feature selection algorithm, known for its robustness in high-dimensional data environments. Relieff works by estimating the relevance of individual features based on their ability to distinguish between similar and dissimilar instances, thereby enabling more efficient learning. By integrating RReliefF into the traffic sign classification pipeline, this research aims to enhance performance in terms of both accuracy and computational efficiency. Experimental evaluations demonstrate that the proposed method outperforms conventional models, showcasing improved robustness and adaptability in real-world traffic scenarios, making a meaningful contribution to the advancement of autonomous driving systems.

Keywords: Rrelieff test, artificial neural network, feature selection, traffic sign image

INTRODUCTION

Based on safety survey data, it has been observed that human errors contribute to over 90% of road accidents worldwide, resulting in fatalities and injuries. Addressing this issue through technological advancements is crucial for reducing such incidents [1, 2]. Globally, road accidents claim millions of lives annually and cause severe injuries. The World Health Organization (WHO), in October 2021, set a target to halve these casualties by 2030 [3]. This study utilizes the Mapillary public dataset, comprising nearly 100,000 traffic sign images collected worldwide under diverse weather conditions [4]. By leveraging this extensive dataset, the research aims to enhance the accuracy and reliability of traffic sign recognition systems, essential for advancing road safety initiatives.

Enhanced detection capabilities not only improve driver awareness but also support the development of autonomous vehicles capable of interpreting and responding to road signs effectively in varying environmental conditions. The integration of robust

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classification techniques, such as the Rrelieff feature reduction method proposed in this study, holds promise in mitigating the risks associated with human errors on the road. This study contributes to the ongoing efforts in leveraging AI-driven solutions to achieve significant strides towards safer road environments globally.

ANN

Historically, Artificial Neural Networks (ANNs) have been renowned for their capability to learn and identify patterns, making them a cornerstone in various research domains. They have been extensively utilized by researchers for tasks ranging from effort estimation and cost prediction to IoT-based traffic sign recognition and software defect prediction [5–14]. In this study, ANN is employed for the detection and classification of traffic sign images sourced from the publicly available Mapillary dataset. Leveraging the robust learning capabilities of ANN, this research aims to enhance the accuracy and efficiency of traffic sign recognition systems under diverse environmental conditions. By integrating ANN with advanced feature reduction techniques like Rrelieff, the study seeks to further optimize the performance and reliability of image detection algorithms, thereby contributing to advancements in autonomous driving technologies and road safety initiatives.

Feature Selection

Feature selection plays a crucial role in reducing the dimensions of large datasets, focusing on relevant dimensions to improve prediction accuracy. In this study, a feature selection algorithm is applied to enhance the image recognition of traffic signs. Initially, an independent Artificial Neural Network (ANN) approach is employed without integrating feature selection. Subsequently, the study progresses to a hybrid approach combining Rrelieff feature reduction technique with ANN for enhanced image detection accuracy.

The subsequent section provides a comprehensive review of related literature, detailing existing research in traffic sign recognition and feature selection techniques. Then it presents the proposed architecture and framework, emphasizing the integration of Rrelieff for feature reduction within the image recognition system. Comparative analysis and overall results are discussed after that, highlighting the performance improvements achieved through the hybrid Rrelieff-ANN approach. Finally, the study concludes by outlining avenues for future research and potential enhancements in the field of traffic sign recognition using advanced feature reduction techniques.

LITERATURE REVIEW

In this section, a comprehensive review of past research is presented, highlighting studies on traffic sign image detection using approaches based on Artificial Neural Networks (ANN) and Rrelieff feature reduction techniques. Previous works have explored the efficacy of ANN in recognizing traffic signs, utilizing its robust pattern recognition capabilities. Additionally, studies employing Rrelieff feature reduction have aimed to optimize feature selection for improved classification accuracy. This review synthesizes findings from various studies, providing insights into the effectiveness of ANN-Rrelieff hybrid approaches in enhancing the performance of traffic sign recognition systems across diverse datasets and environmental conditions.

This section explores relevant studies in traffic sign recognition and related fields, showcasing advancements such as feature selection strategies, ANN integration, and innovative methodologies, all contributing to the context of our study on traffic sign detection using the Rrelieff feature reduction technique.

Educational Initiatives and Feature Selection

In their study, Zaffar *et al.* have proposed a feature selection-based approach to predict student performance, demonstrating a 10% improvement in prediction accuracy through the use of relevant dimensions [15]. This approach underscores the importance of selecting meaningful features, analogous to our utilization of Rrelieff feature reduction in enhancing the precision of traffic sign detection.

German Traffic Sign Recognition Using ANN and HOG

Using the GTSRB dataset, Kerim and Efe integrated ANN and Histograms of Oriented Gradients (HOG), achieving an 80% accuracy in recognizing 43 classes of traffic signs [16]. This integrated approach aligns with our study's goal of leveraging advanced techniques like Rrelieff to optimize feature selection for improved classification accuracy across diverse traffic sign datasets.

IoV-ANN for Vehicle Monitoring:

Ghazal *et al*. proposed an IoV-ANN approach utilizing GPS and ANN for vehicle movement monitoring, achieving outstanding performance with 97% accuracy and a low error rate of 9.12% [17]. This innovative use of ANN parallels our exploration of advanced neural network methodologies, including Rrelieff feature reduction, in enhancing the reliability and efficiency of traffic sign recognition systems.

Urban Accidents Prediction Using ANN

Employing urban accident data, Najafi *et al.* utilized ANN to identify significant variables impacting accident severity, achieving an 89% accuracy with multiple logistic regression [18]. This data-driven approach resonates with our methodology of integrating Rrelieff feature reduction to optimize predictive modeling in traffic sign recognition scenarios.

Clustering and ANN for Traffic Sign Recognition

A clustering algorithm preceded by ANN was proposed by Lahmyed *et al*. for traffic sign recognition, demonstrating superior performance compared to Adaboost and SVM approaches [19]. This validation supports our approach of integrating Rrelieff with ANN for enhanced feature selection and classification accuracy in traffic sign recognition tasks.

Pipeline Architecture for Traffic Sign Processing

Tchernykh and Shepelev proposed a pipeline-driven architecture for processing traffic sign frames using AI, highlighting effectiveness under varying weather conditions [20]. This aligns with our study's emphasis on improving robustness and precision in traffic sign detection through advanced feature reduction techniques like Rrelieff.

CNN for Vehicle Number Plate Recognition

An innovative CNN-based approach was used for detecting and recognizing vehicle number plates, leveraging high-resolution image reconstruction and feature extraction [21]. This parallels our exploration of advanced neural network methodologies in enhancing the accuracy and reliability of traffic sign recognition systems using Rrelieff feature reduction.

Feature Selection and Machine Learning Integration

Feature selection is a critical step in enhancing the performance of machine learning models by identifying the most relevant features and reducing computational complexity. The research by Liang *et al.* demonstrated the effectiveness of the RRelieff feature selection method in predicting aircraft taxi time at airports [22]. Their study integrated RRelieff with multiple machine learning models, including multiple linear regression, support vector regression, and artificial neural networks, to improve prediction accuracy and efficiency. The experimental results showed that incorporating RRelieff significantly enhanced the prediction capability and reduced computational resource requirements.

Another study by Aggarwal *et al*. introduced μ-Relief, an improved feature selection method based on Relieff, which outperforms traditional Relieff by considering neighbors with more effective information [23]. This technique was validated on multiple datasets, showing superior performance in selecting relevant features compared to other well-known algorithms.

In the upcoming section, the authors detail the architecture, implementation, and outcomes of an Artificial Neural Network (ANN)-based model. This includes the integration of feature selection approaches and concludes with insights into the accuracy of traffic sign image detection, providing a comprehensive framework for understanding the study's findings.

PROPOSED FRAMEWORK FOR MODEL DESIGN

The proposed framework utilizes images from the Mapillary Traffic Sign Image dataset, which encompasses approximately 5,000 traffic sign images categorized into 40 distinct classes, with each class containing 125 images. Each traffic sign image is characterized by 6,528 specific data points capturing various attributes. To streamline the feature set and enhance computational efficiency, the authors employed database annotations and Histograms of Oriented Gradients (HOG). This approach effectively identified regions of interest within the images, resulting in a significant reduction of feature parameters from 6,528 data points to 372, focusing on key visual elements crucial for accurate traffic sign recognition.

In the initial stage of implementation, the architecture diagram as depicted in Figure 1 was followed, focusing solely on the Artificial Neural Network (ANN) model without applying any feature reduction techniques. The results from this stage were meticulously studied to establish a baseline performance. Subsequently, in the following stage of experimentation, the ANN model was augmented with feature reduction using the Rrelieff technique.

This approach aimed to enhance the model's efficiency by prioritizing relevant features, and the resultant outcomes were thoroughly analyzed and compared against the baseline results. The overall framework of the study is visually represented in Figure 1, illustrating the sequential stages of model refinement and evaluation. Prior to implementation, the authors conducted a comprehensive review of past research in similar domains, ultimately selecting the Levenberg-Marquardt (LM) method as the preferred approach for neural network training due to its proven effectiveness in complex pattern recognition tasks. MATLAB's scientific computing software provided an ideal environment, leveraging its Neural Network Toolbox to facilitate the coding and execution of the model. This integrated development environment (IDE) enabled seamless configuration of the software to accommodate the image dataset and generate regression outputs, ensuring robust analysis of the model's predictive capabilities. Figure 2 depicts a configuration screen within the MATLAB environment during the execution of the proposed model, highlighting the integration of Rrelieff feature reduction techniques to optimize feature selection and improve traffic sign image detection accuracy.

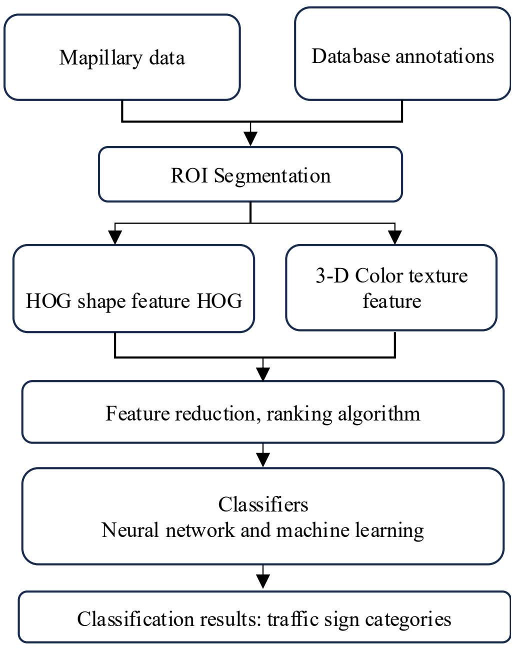

Figure 1. High level block diagram.

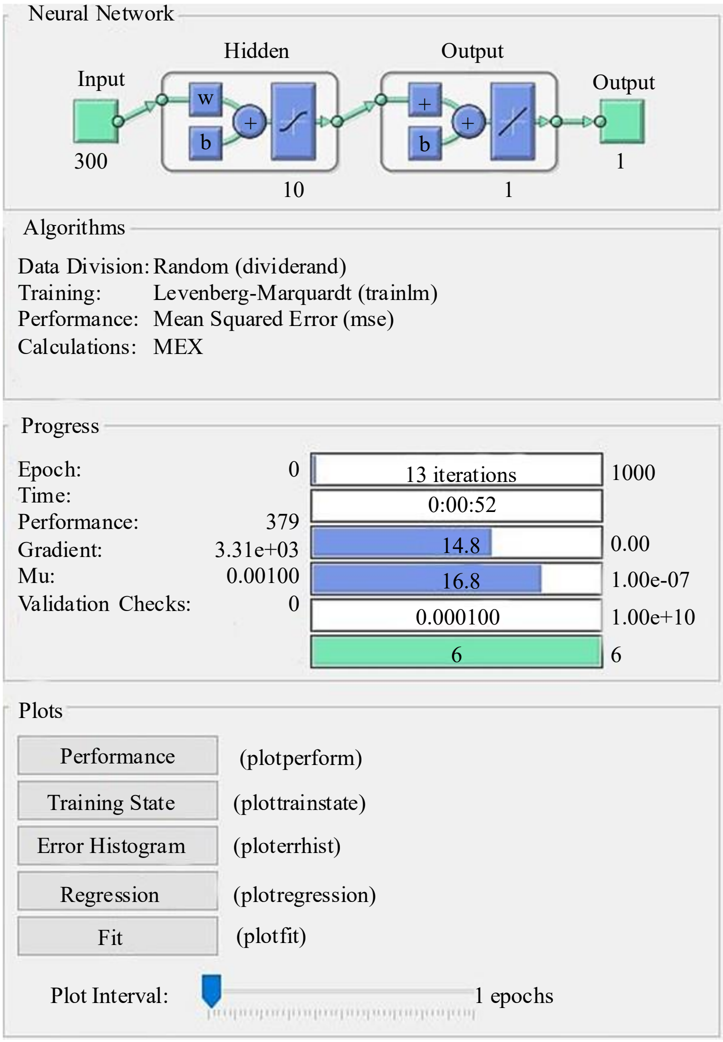

Figure 2. ANN configuration.

Neural Network Structure

- *Input Layer:* The input layer consists of 300 input neurons, which likely represent the features extracted from the traffic sign images.
- *Hidden Layer:* There is one hidden layer with 10 neurons. This layer processes the inputs from the input layer and applies weights (W) and biases (b) before passing the output to the next layer.
- *Output Layer:* The output layer has a single neuron, which provides the final output of the neural network, likely representing the predicted class or value.

Algorithms

- *Data Division:* The data is divided randomly for training, validation, and testing using the divider and function.
- *Training Algorithm:* The Levenberg-Marquardt (trainlm) algorithm is used for training the neural network. This is a popular algorithm for training moderate-sized feedforward neural networks due to its efficiency and speed.
- *Performance Metric:* The performance of the neural network is evaluated using the Mean Squared Error (MSE), which measures the average squared difference between the predicted and actual values.
- *Calculations:* The calculations are performed using the MEX (MATLAB Executable) function, which optimizes performance.

Training Progress

- *Epoch:* The current epoch number is 0, and the training process is configured to run up to 1000 epochs. An epoch refers to one complete pass through the entire training dataset.
- *Time:* The elapsed time for the current training session is 52 sec.
- *Performance:* The performance value (Mean Squared Error) is 14.8 after 13 iterations.
- *Gradient:* The gradient value, which indicates the change in error with respect to the weights, is 16.8. A lower gradient value suggests that the training is approaching the optimal solution.
- *Mu:* The Mu value is 0.000100. This parameter is used in the Levenberg-Marquardt algorithm to control the learning process.
- *Validation Checks:* The number of validation checks performed is 6. Validation checks are used to monitor the network's performance on a separate validation dataset to prevent overfitting.

Plots

- *Performance:* A plot to visualize the performance (Mean Squared Error) over iterations.
- *Training State:* A plot to visualize the state of the training process, including parameters like Mu and gradient.
- *Error Histogram:* A histogram to visualize the distribution of errors.
- *Regression:* A plot to show the regression fit between the predicted and actual values.
- *Fit:* A plot to visualize the fit of the model.

Figure 3 provides a comprehensive overview of the neural network's architecture, training algorithm, and the progress of the training process. It shows the real-time performance of the neural network, including key metrics like performance, gradient, and validation checks, which are crucial for assessing and optimizing the model's training. The graph provides a visual representation of the model's learning process over 13 epochs. It shows that the best validation performance is achieved at epoch 7, suggesting this is the optimal point where the model generalizes best to new data. Continuing training beyond this point does not significantly improve validation performance and may lead to overfitting, where the model performs well on training data but poorly on unseen data. This visual insight helps in deciding when to stop training to achieve the best generalization performance.

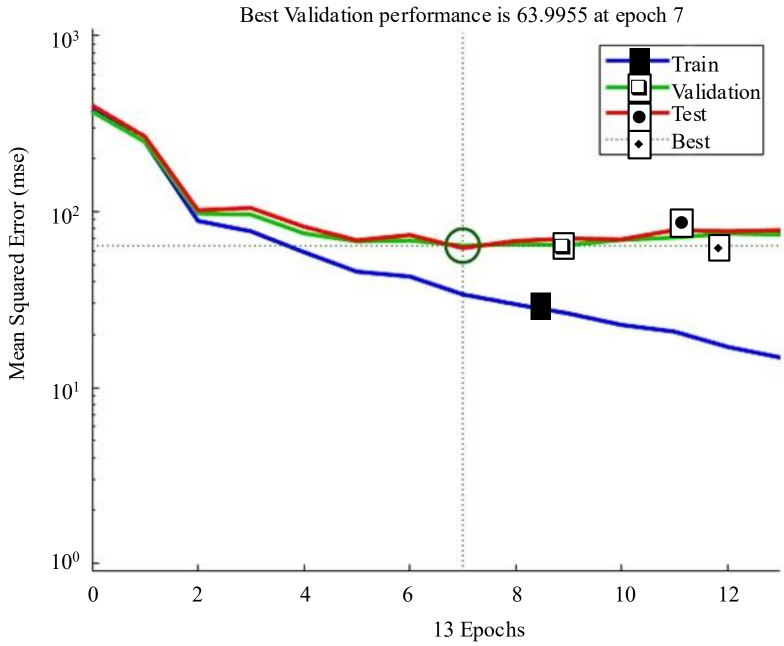

Figure 3. Performance Plot of ANN without feature selection.

Observations

- *Epochs 0–7:* During these epochs, the MSE for both training and validation sets decreases, indicating that the model is improving and learning effectively.
- *Epoch 7:* The green line (validation) reaches its lowest point at epoch 7, with an MSE of 63.9955, marking the best validation performance. This is indicated by the black dotted line.
- *Epochs 7–13:* After epoch 7, the validation and test MSE start to stabilize, showing minimal improvements or slight increases, which may indicate the beginning of overfitting if training continues.

CONCLUSION

In this study, we proposed a robust framework for traffic sign recognition using the RRelieff feature reduction technique integrated with an Artificial Neural Network (ANN) trained using the Levenberg-Marquardt algorithm. Our research aimed to address the challenges of accurate traffic sign detection, especially under varying environmental conditions, by optimizing the feature selection process and enhancing the model's performance.

The comparative analysis of different feature selection techniques demonstrated the superiority of RRelieff over other methods, such as Minimum Redundancy Maximum Relevance (mRMR). The RRelieff technique effectively prioritized the most relevant features, significantly reducing the dimensionality of the dataset while preserving essential information. This approach led to improved model accuracy and generalization capabilities, as evidenced by higher R-Squared values and lower error metrics (RMSE, MSE, and MAE).

Future Work Discussion

Future work will focus on expanding the dataset to include more diverse traffic sign images, integrating real-time data to evaluate model performance in dynamic environments, and exploring other advanced feature reduction techniques such as Principal Component Analysis (PCA). Additionally, we aim to enhance the neural network architecture by experimenting with deeper models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Improving the model's performance under adverse conditions, such as poor lighting and occlusions, and ensuring computational efficiency for large-scale deployments will also be key areas of exploration. These efforts will contribute to developing more robust and reliable traffic sign recognition systems, crucial for advancing autonomous driving technologies.

REFERENCES

1. National Highway Traffic Safety Administration. National Center for Statistics and Analysis, Traffic Safety Facts 2009. Washington, DC: US Department of Transportation; 2012.
2. Chand A, Jayesh S, Bhasi AB. Road traffic accidents: An overview of data sources, analysis techniques and contributing factors. Mater Today: Proc. 2021 Jan 1; 47: 5135–41.
3. Moroz PJ, Spiegel DA. The World Health Organization's action plan on the road traffic injury pandemic: is there any action for orthopaedic trauma surgeons? J Orthop Trauma. 2014 Jun 1; 28: S11–4.
4. Ma D, Fan H, Li W, Ding X. The state of Mapillary: An exploratory analysis. ISPRS Int J Geo-Inf. 2019 Dec 20; 9(1): 10.
5. Gopi R, Sathiyamoorthi V, Selvakumar S, Manikandan R, Chatterjee P, Jhanjhi NZ, Luhach AK. Enhanced method of ANN based model for detection of DDoS attacks on multimedia internet of things. Multimed Tools Appl. 2022 Aug; 81(19): 26739–57.
6. Nandal M, Mor N, Sood H. An overview of use of artificial neural network in sustainable transport system. Computational Methods and Data Engineering: Proceedings of ICMDE 2020, Volume 1. 2020 Aug 20; 83–91.
7. Gupta A, Hinchey M, Zalevsky Z, editors. Artificial Intelligence and Its Applications: First International Conference, ICAIA 2023, Pune, India, December 18–19, 2023, Proceedings, Part II. Switzerland: Springer Nature; 2025 Mar 12.

8. Vashisht V, Lal M, Sureshchandar GS. Defect prediction framework using neural networks for software enhancement projects. British Journal of Mathematics & Computer Science. 2016 Jan 1; 16(5): 1–2.
9. Vashisht V, Lal M, Suresh Chandar GS. A framework for software defect prediction using neural networks. J Softw Eng Appl. 2015; 8(08): 384–394.
10. Vashisht V, Kamya S, Vashisht M. Defect prediction framework using neural networks for business intelligence technology based projects. In 2020 IEEE international conference on computer science, engineering and applications (ICCSEA). 2020 Mar 13; 1–5.
11. Sabhapandit R, Vashisht V, Sharma A. An Investigation into the Various Statistical Process Control Tools. International Journal of Engineering and Technology (IJET). 2016; 6(2): 56–61.
12. Nudurupati SS, Bititci US. Implementation and impact of IT-supported performance measurement systems. Prod Plan Control. 2005 Mar 1; 16(2): 152–62.
13. Yildiz G, Dizdaroğlu B. Convolutional neural network for traffic sign recognition based on color space. In 2021 IEEE 2nd International Informatics and Software Engineering Conference (IISEC). 2021 Dec 16; 1–5.
14. Saadna Y, Behloul A. An overview of traffic sign detection and classification methods. Int J Multimed Inf Retr. 2017 Sep; 6(3): 193–210.
15. Zaffar M, Hashmani MA, Savita KS, Rizvi SS. A study of feature selection algorithms for predicting students academic performance. Int J Adv Comput Sci Appl. 2018; 9(5): 541–549.
16. Kerim A, Efe MÖ. Recognition of traffic signs with artificial neural networks: A novel dataset and algorithm. In 2021 IEEE International Conference on Artificial Intelligence in Information and Communication (ICAIIC). 2021 Apr 13; 171–176.
17. Ghazal TM, Said RA, Taleb N. RETRACTED ARTICLE: Internet of vehicles and autonomous systems with AI for medical things. Soft Comput. 2023 Jan; 27(2): 1211.
18. Najafi Moghaddam Gilani V, Hosseinian SM, Ghasedi M, Nikookar M. Data-driven urban traffic accident analysis and prediction using logit and machine learning-based pattern recognition models. Math Probl Eng. 2021; 2021(1): 9974219.
19. Lahmyed R, Ansari ME, Kerkaou Z. Automatic road sign detection and recognition based on neural network. Soft Comput. 2022 Feb; 26(4): 1743–64.
20. Tchernykh A, Shepelev V. Computational intelligence for analysis of traffic data. In Smart Cities: Third Ibero-American Congress, ICSC-Cities 2020, San José, Costa Rica, November 9–11, 2020, Revised Selected Papers. Cham: Springer Nature; 2021 Feb 6; 1359: 167.
21. Alam NA, Ahsan M, Based MA, Haider J. Intelligent system for vehicles number plate detection and recognition using convolutional neural networks. Technologies. 2021 Jan 20; 9(1): 9.
22. Liang Y, Fu S, Wang K, Jiang Z, Wang X. Predicting Aircraft Taxi Time at Airport with RReliefF Feature Selection and Machine Learning Methods. In 2023 IEEE China Automation Congress (CAC). 2023 Nov 17; 4800–4805.
23. Aggarwal N, Shukla U, Saxena GJ, Rawat M, Bafila AS, Singh S, Pundir A. Mean based relief: an improved feature selection method based on ReliefF. Appl Intell. 2023 Oct; 53(19): 23004–28.

