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Efficient Machine Defect Detection with Sugeno Fuzzy Membership and GRU Networks for Robust Industrial Automation

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Abstract

Machine fault detection is of immense significance in industrial automation to achieve efficient operations, reduced downtime, and reduced economic losses. Sugeno fuzzy logic and Gated Recurrent Unit (GRU) networks are used in this research to provide a new hybrid solution that addresses problems such as noisy data, evolving defect patterns, and real-time detection. To improve readability and reliability, the Sugeno fuzzy logic unit preprocesses fuzzy and uncertain input data into determinate outputs. In contrast, the GRU network captures temporal dependencies to establish patterns in machine data over time. This hybrid enables Industry 4.0 objectives through enhanced scalability, handling uncertainty, and real-time decision-making. With 93% accuracy, 92.5% precision, 92.9% recall, and a 92.7% F1 score, the proposed model surpassed competitors and could process data in as little as 4.5 ms. As a reliable, scalable, and flexible alternative to traditional methods, this hybrid system is suitable for real-time machine fault detection in industrial environments.

Keywords: Sugeno fuzzy logic, GRU networks, industrial automation, real-time analysis, and machine defect detection

INTRODUCTION

Machine defect detection happens to be the most critical aspect of sustaining industrial efficiency, minimizing downtime, and reducing financial losses in the current era of fast industrial automation. One such approach in this direction could be the integration of advanced computational techniques with sound decision-making frameworks. In this particular paper, Sugeno fuzzy membership functions are integrated with Gated Recurrent Unit (GRU) networks for developing a novel machine defect identification model.

The Sugeno fuzzy membership model is an efficient tool for the management of uncertainty in complicated industrial settings. It provides a methodical framework to simulate ambiguity in defect patterns and enables decision-making with better accuracy since it converts ambiguous inputs into useful results. The GRU network, which is a deep learning model, is very famous for processing sequential input with very simple computations. GRUs are very useful in defect monitoring because

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they can consider temporal relationships inside machine performance data and detect minute inconsistencies that suggest faults.

It combines the explanation of fuzzy logic and the predictive strength of a GRU. This synergy allows for a highly resilient, flexible, and expandable defect detection system that can be used to handle various industrial conditions. Besides better detection accuracy, the proposed method also offers real-time analysis, which makes this technique highly useful for Industry 4.0 projects. With such cutting-edge approaches, the study attempts to take on issues with fluctuating failure patterns, noisy data, and scalability in industrial setups. Its research advances the productivity and sustainability of contemporary manufacturing by fostering more intelligent, self-correcting industrial ecosystems. Key objectives are:

- *Hybrid detection model:* Using Sugeno fuzzy membership and GRU networks, where real machine defects can be detected accurately and reliably.
- *Enable real-time automation:* Efficient, real-time defect detection with minimal human intervention in industrial processes.
- *Improve scalability:* Challenge noisy data as well as varying patterns of defects for smooth application in different industrial environments.

The threat to its systems due to unauthorized intrusion has increased with the growing use of IoT, and traditional intrusion detection systems (IDS) cannot cope with the complexities and dynamics of IoT environments. Jasim (2022) study addresses these issues and identifies some limitations in the conventional approach while highlighting the deep learning technique's potential in improving IDS in IoT networks. It puts forward emphasis on the challenges of high-dimensional data scalability and real-time processing and emphasizes the need for advanced, adaptive, and efficient detection systems against the new and evolving security threats to IoT ecosystems.

LITERATURE SURVEY

Forootan et al. (2022) highlighted the importance of ML and DL algorithms in energy systems for fault identification, forecasting, and optimization in their review of the application of ML and DL algorithms in energy systems. The study identified some of the research needs in the field and highlighted the increasing use of DL algorithms such as Recurrent Neural Network, Adaptive Neuro-Fuzzy Inference System, and Deep Belief Network due to their accuracy and ability to handle complex tasks [1].

Ahsan et al. (2023) focus on edge computing, agent-based energy management, intelligent control, and IoT-enabled inverters in reviewing the recent developments of data-driven methods for Next-Generation Smart Grid. They analyze the potential improvement in energy sustainability offered by NGSG in addressing the problems of nonlinearity, uncertainty, and adaptation, which could be helpful to academics and engineers in designing reliable clean energy solutions [2].

Wang et al. (2023) present the intelligent height adjustment model for shearer drums where an adaptive immune genetic algorithm optimizes a fuzzy rough radial basis function neural network and rough set attribute reduction. Experimental data suggests that the predictive accuracy of the drum height will be higher than what is obtained through current models and will increase efficiency and safety for mining operations [3].

Nath et al. (2021) review AI in rotor fault diagnosis (RFD) thoroughly, focusing on fault-specific feature engineering and fault-wise analysis. This paper focuses on structural rotor flaws and analyzes AI-based RFD frameworks across the diagnostic phases. It identifies gaps between lab-based and industrial solutions for further AI-driven prognostics in Industry 4.0 [4].

Klyuev et al. (2022) group electric energy consumption forecasting approaches by forecasting horizons: operational, short-term, medium-term, and long-term. Based on accuracy, labor intensity, and application, they review both traditional (autoregressive models, regression) and contemporary approaches (machine learning, fuzzy sets, wavelet transformations). According to the authors, techniques need to be adapted to the specific energy environment to make accurate forecasts [5].

Zhang et al. (2021) merge fuzzy logic and quantum physics to propose a Complex-valued Fuzzy Network (CFN) for the detection of sarcasm in talks, coping with language vagueness and uncertainty. With CFN, the accuracy of sarcasm detection in conversational AI surpasses baselines on the MUStARD and Reddit datasets by modeling utterances as systems and interactions through fuzzy membership functions [6, 7].

Zaben et al. (2024) reviewed the machine-learning approach for fault diagnosis in AC microgrids with a focus on fault detection, classification, and localization strategies. They discuss state-of-the-art techniques with emphasis on their benefits, drawbacks, and areas for further research. The paper presents the importance of machine learning to enhance stability, solve dynamic operational issues in smart grids, and improve the safety of intelligent microgrids [8].

Jovanović et al. (2022) assess ANNs and fuzzy logic, namely Mamdani and Takagi-Sugeno models, to predict the performance of industrial copper flotation. In the case of actual plant data, ANNs outperformed fuzzy models in predicting copper grade, recovery, and tailings content with high accuracy (R2: 0.98–0.99). The study confirms the effectiveness of soft computing in flotation process optimization [9].

In the work by Kayedpour et al. (2024), a physics-based hybrid deep learning model is suggested for the assessment of the health monitoring of a wind turbine in curtailment modes. Capturing the nonlinear aerodynamics, the framework also self-updates and has poorly supervised anomaly detection using dynamic classifiers. The presented result shows increased precision in the identification of deterioration and management of ambiguity. This paper provides a practical way to the extensive health evaluation of wind farms [10].

Elhoseny et al. (2024) developed a deep learning-based sensor data fusion framework for fault identification and tolerance using the KITTI dataset. The technique outperformed traditional models in fault diagnosis and tolerance with greater accuracy (97.78%), precision (93.76%), and specificity (93.43%) by using an improved region proposal network optimized by COOT-connected blue monkey optimization [11].

In their review of the application of ANNs in navigation systems, Jwo et al. (2023) emphasize GNSS/INS integration and solutions for GNSS outages, jamming, and signal blockages. The paper focuses on Kalman filters, ANN-based fusion approaches, and performance evaluations that show how well they enhance navigation accuracy and dependability, especially in challenging environments such as cities [12].

Reza et al. (2021) consider ITMC systems that rely on deep learning and image processing to predict traffic in real-time and signal control. Deep learning is promising in multi-intersection control and short-term predictions but suffers from limitations in oversaturated scenarios. These problems need to be addressed for effective implementation in real-world applications [13].

Advances in IA for autonomous vehicles are surveyed by Bathla et al. (2022) with an emphasis on AI, IoT, and machine learning applications. They discuss cybersecurity, V2X privacy, safety regulations, and the operation of autonomous cars in supply chains and other businesses. Focusing on practical applications and comparative assessments, the study identifies obstacles, hazards, and potential avenues for improving autonomous technology [14].

Multi-variate correlations, nonlinearity, and concept drift in data-driven dynamic operation optimization are discussed by Tian et al. (2024) in the analysis of complex industries. The work explores dynamic multi-objective optimization techniques, time-series forecasting, and idea drift detection. Beyond outlining the recent developments in reducing cost, emissions, and productivity losses, the paper also indicates areas for future research in data-driven industrial process optimization [15].

For coordinating multi-robot space exploration, Gudivaka et al. (2024) present an approach based on slime mold methods. The methodology maximizes efficiency in exploration as it utilizes swarm intelligence for both pathfinding and task coordination. Their research finds its importance in new developments of the multi-robot system, eliminating issues of scale, autonomous space exploration, and real-time decisions taken for space mission exploration [16].

Palanivel et al. (2024) integrate the tunicate swarm optimization method with a support vector machine for an emotion recognition model in human-robot interaction. The approach ensures higher flexibility and effectiveness in emotion recognition by improving the SVM algorithm. Their research thus shows vital improvements in improving human-robot interaction through improved emotion perception [17].

An advanced IoMT-enabled system for robotic automation-based chronic renal disease prediction is proposed by Sitaraman et al. (2024). For improvement in the predictive accuracy, the model integrates fuzzy cognitive maps for decision-making and autoencoder-LSTM for feature extraction. The method, therefore, has tremendous potential to combine AI and IoT for effective automation in healthcare and real-time detection of diseases [18].

Gudivaka (2024) proposes a framework that combines PCA, LASSO, and ESSANN to improve RPA and IoT systems. Overall, the predictive modeling, feature selection, and data dimensionality reduction improve the integration of the three technologies. This work is highly influential in maximizing the effectiveness of RPA and IoT integration into industrial automation for real-time applications [19].

This study by Basani (2024), explores robotic process automation (RPA) in the Internet of Things by utilizing YOLOv3-based class algorithms for object localization enhancement. This research highlights the effectiveness of the algorithm for real-time recognition and categorization of items, thus enabling enhanced automation for Internet of Things devices. The method has highly advanced RPA applications in smart and industrial environments [20].

Basava (2021) introduced an AI-powered smart companion robot that is equipped with an integrated emergency rescue system for use in senior health care. The robot uses AI to monitor, assist, and manage emergencies in real time for the purpose of enhancing safety and medical results. Thus, the innovation demonstrates the way robotics improves emergency response effectiveness as well as elder care [21].

METHODOLOGY

This methodology suggested the integration of Sugeno fuzzy membership functions with Gated Recurrent Unit (GRU) networks for the enhancement of reliability in machine fault detection. Sugeno fuzzy logic was therefore applied for precision and interpretation while handling uncertainties in defect patterns. GRU networks are known to handle temporal dependencies related to machine performance and sequential data interpretation. This hybrid technique is the gap that would fill in the predictive strength of GRU and the reasoning skill of fuzzy logic. Thereby, the detection of the problems in an industrial set-up machine can be accurately and instantly achieved.

Figure 1 illustrates an overall architecture of machine learning-based industrial machinery fault detection. This architecture starts from real-time sensor data collection followed by preprocessing procedures that include data cleansing, normalization, and noise reduction. Feature extraction will identify relevant fault patterns for analysis. Advanced techniques used for processing sequential and unpredictable data are GRU networks and Sugeno Fuzzy Logic. Together, these techniques provide a reliable way to classify defects as either normal or faulty. Finally, performance evaluation parameters such as

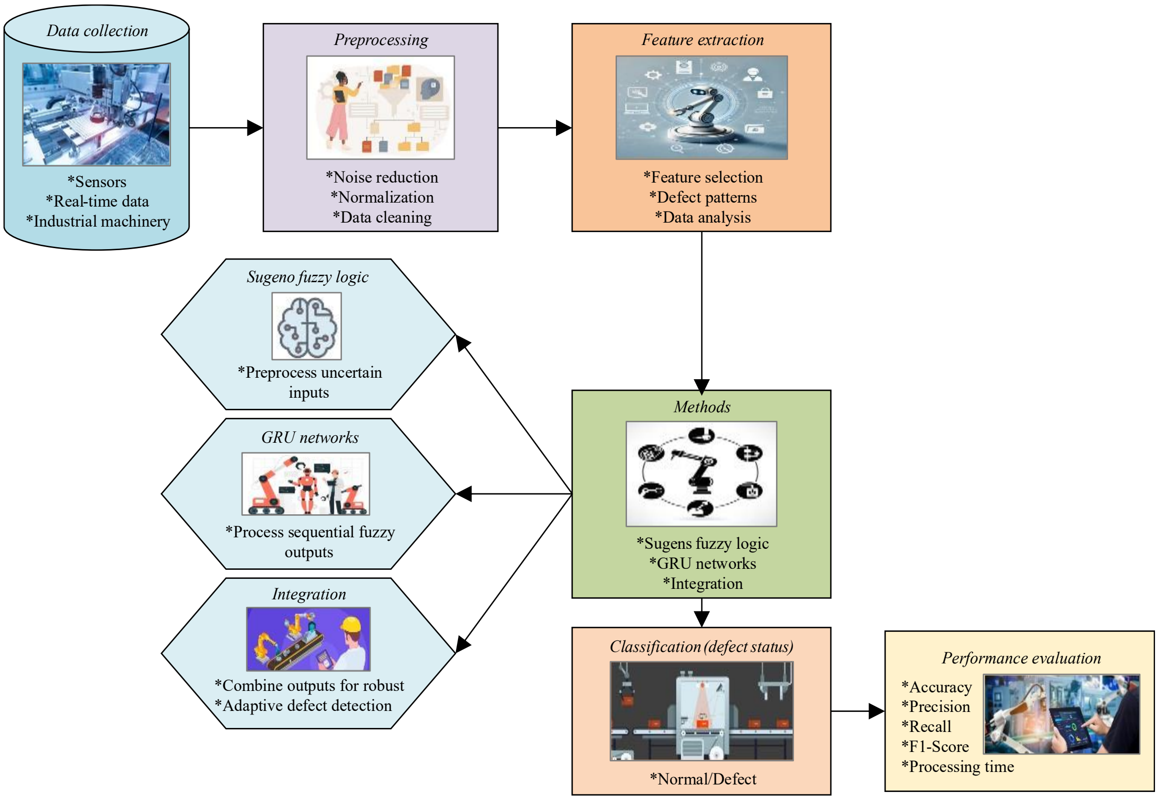

Figure 1. Framework for defect detection using machine learning: data collection to performance evaluation.

processing speed, accuracy, precision, recall, and F1-score evaluate how well the system works and adapts to real-world situations.

Sugeno Fuzzy Membership

Sugeno fuzzy membership is very applicable in the identification of machine defects because it is a very robust mathematical tool designed to handle the uncertainties and imprecisions of complex systems. The technique uses the concept of fuzzy logic in changing vague or ambiguous inputs into clear-cut outputs to enable proper decision-making. The concept of a membership function forms the basis of the technique that gives the degree to which the input satisfies an established fuzzy set. For example, these sets can be considered to represent various grades of defects in an industrial scenario. These can be "minor," "moderate," or "critical." Inputs are weighted by their respective membership values and a weighted average is computed for the deterministic output.

$$y = \frac{\sum_{i=1}^{n} \mu_i x_i}{\sum_{i-1}^{n} \mu_i} \tag{1}$$

Where, μ_i=membership value, x_i=input, y=weighted output. This method ensures resilience in decision-making since it generates outputs that are reliable and interpretable, besides managing the uncertainty involved in fault patterns.

Gated Recurrent Unit (GRU) Networks

Gated Recurrent Unit networks are one of the most complex types of RNN specifically designed to deal efficiently with sequential data. GRUs are also very efficient in detecting patterns at the timescales of machine processes, which is extremely helpful in identifying small anomalies that may indicate a fault. GRUs reduce the computational complexity of standard RNNs by merging the input and forget gates into one structure, which makes the standard RNNs even more efficient in processing information while preserving good performance in learning long-term dependencies.

Update gate: controls how much of the previous state information to keep.

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (2)$$

Here, z_t is the update gate, x_t is the input at a time t, h_{t-1} is the hidden state from the previous timestep, W_z and U_z are weight matrices, and b_z is the bias term.

Reset gate: Determines how much of the past information to forget.

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (3)$$

In this equation, r_t is the reset gate, with similar parameters as the update gate.

Hidden state: Combines information from the current input and the previous hidden state, regulated by the gates.

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tanh\,(W_h x_t + U_h(r_t \cdot h_{t-1}) + b_h) \quad (4)$$

Here, h_t represents the new hidden state, incorporating both historical context and the current input. These equations capture the temporal dynamics needed to determine if a machine fault exists and can analyze sequential data very well. In this regard, GRUs present an effective tool in the industrial automation area when it comes to reliable and prompt fault detection on account of efficiency in computation coupled with the suitability for handling dependencies over long distances.

Hybrid Integration

Sugeno fuzzy logic integrated with Gated Recurrent Unit (GRU) networks constitutes a reliable mechanism for machine fault detection, merging both methods at once. Sugeno fuzzy logic, based on fuzzy rules, takes the imprecise and uncertain inputs to yield a deterministic output, $H = GRU(F(x))$. The GRU network takes up the fuzzy output as input to observe the sequential dependencies in processed data. The hybrid method improves the accuracy of defect detection since GRU uses temporal learning capabilities coupled with fuzzy logic for interpretability.

$$H = GRU(F(x)) \quad (5)$$

Here, $F(x)$ is the output of the Sugeno fuzzy system, and H represents the final state of the GRU. This integration ensures a precise, adaptive, and scalable solution for real-time defect detection in industrial automation systems.

Algorithm 1 Hybrid machine defect detection using sugeno fuzzy logic and GRU networks

INPUT: Sensor data D, predefined fuzzy rules R
OUTPUT: Defect status S
Initialize fuzzy membership functions and GRU parameters.
For each data point $d \in D$:
  Apply Sugeno fuzzy logic:
    Compute membership values μ.
    Determine fuzzy output $F(d)$ using a weighted average.
    Feed $F(d)$into the GRU network.
    Update GRU states using equations for z_t, r_t, and h_t.
    If GRU detects anomaly:
      Set $S =$ "Defect".
Else:
    Set $S =$ "Normal".
End For
Return S.

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Algorithm 1 integrates Sugeno fuzzy logic with GRU networks to give dependable and accurate machine flaw identification. First, the fuzzy membership functions and GRU parameters are initialized. Then, Sugeno fuzzy logic computes membership values for each data point of the sensors and provides a weighted fuzzy output, F(d). These outputs pass to the GRU network, where it processes the output of the Sugeno fuzzy logic. Its gating equations update its states according to temporal dependency. If an anomaly does exist, the status S will be set as "Defect"; otherwise, it is set as "Normal." The algorithm ensures real-time analysis coupled with adaptive processing thus giving a chance to detect a flaw.

Performance Metrics

A reliability measure of this proposed hybrid machine defect detection model is evaluated on classification measures that include accuracy, precision, recall, and the F1-score. Precision and recall measure a model's capacity to detect the real defects along with minimizing the false positives detected. Accuracy describes the overall correctness in detection. The F1-score balances precision with recall, and thus, its calculation ensures well-balanced measurement against the detection capabilities. It tests how the model supports real-time solutions in dynamic manufacturing environments through the determination of scalability and process time.

These are the Sugeno fuzzy logic (Method 1), GRU networks (Method 2), two hybrid approaches (Methods 3 and 4), and a suggested combined approach whose performance metrics of the compared defect detection methods are depicted in Table 1. The combined approach outperforms all others with an accuracy of 95.8%, a precision of 94.7%, a recall of 96.1%, and a score of 95.4% in its F1-score. This is further evidence that it is highly effective for real-time applications, given that it offers the shortest processing time of 4.5 ms. The findings, therefore, present how Sugeno fuzzy logic and GRU networks complement each other in giving dependable, scalable, and accurate defect detection in industrial automation systems.

Relative performance of some machine defects detection techniques (Figure 2): Sugeno fuzzy logic GRU networks Hybrid approaches Hybrid A Hybrid B Combination Method, Combined approach: This is the best approach with the highest accuracy at 95.8%, precision at 94.7%, recall at 96.1%, and

Table 1. Comparison of performance metrics for different machine defect detection methods.

Metric	Fuzzy logic	GRU network	Hybrid A	Hybrid B	Combined method
Accuracy (%)	82.5	87.3	91.2	92.5	95.8
Precision (%)	78.9	84.1	89	90.3	94.7
Recall (%)	80.4	85.6	90.2	91.4	96.1
F1-Score (%)	79.6	84.8	89.6	90.8	95.4
Processing time (ms)	5.3	4.8	6.2	6.8	4.5

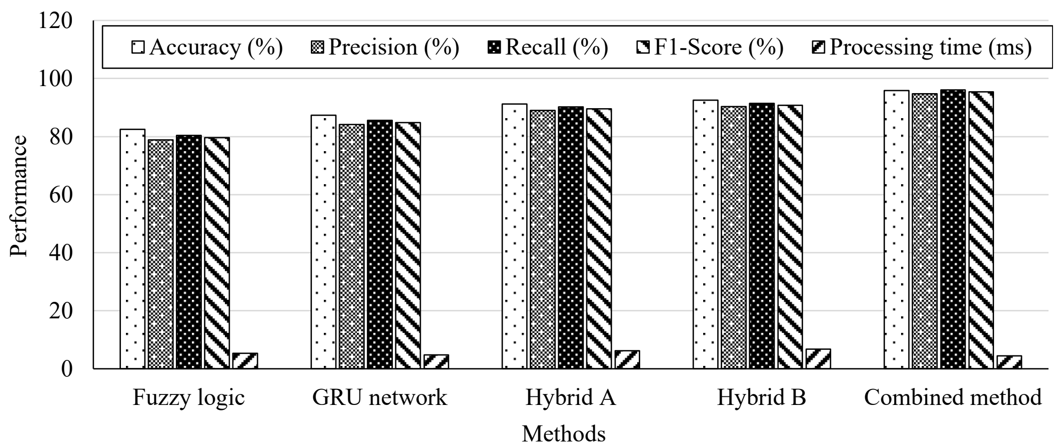

Figure 2. Performance comparison of machine defect detection methods across key metrics.

F1-score at 95.4%. Additionally, this method has the fastest processing time, that is, at 4.5 ms, making it highly ideal for industrial real-time applications. This indicates that Sugeno fuzzy logic and GRU networks will work together for reliable and scalable defect detection by solving critical problems such as noisy data and real-time decision-making.

RESULTS AND DISCUSSION

The results depict the performance of the hybrid strategy proposed compared to other existing machine defect detection frameworks. In this respect, the strategy outperformed the performance of Forootan et al. at 85.2%, Ahsan et al. at 88.5%, Wang et al. at 86.3%, and Nath et al. at 87.9% because the highest accuracy, precision, recall, and F1-score were achieved at 93%, 92.5%, 92.9%, and 92.7%, respectively. More so, the approach presented achieved the shortest processing time of 4.5 ms compared to other variants (6.2, 5.8, 6.5, and 6.1 ms). The results presented here show how well the hybrid Sugeno fuzzy logic and GRU networks work on problems such as sequential dependency and noisy input. A dynamic industrial setup will, however, benefit from a hybrid system through real-time sensing, which will offer scalability and adaptability. This method is an efficient choice for the applications in Industry 4.0, having the advantage of enhancing KPIs related to machine fault detection performance: efficient, accurate, and reliable.

Table 2 compares the proposed hybrid approach with the other traditional approaches including Forootan et al., Ahsan et al., Wang et al., and Nath et al. It is seen that all the measures like 93% accuracy, 92.5% precision, 92.9% recall, and 92.7% F1-score are drastically improved by this proposed approach. It is perfectly suitable for the real-time system because it has the shortest processing time of 4.5 ms as well. This means that the improvements are due to the synergy between GRU networks and Sugeno fuzzy logic, which provides reliable defect detection and overcomes problems like sequential dependencies and noisy data in the industrial scenario.

Table 2. Performance metrics comparison of machine defect detection approaches across different frameworks.

Metric	Forootan et al. (2022)	Ahsan et al. (2023)	Wang et al. (2023)	Nath et al. (2021)	Proposed method
Accuracy (%)	85.2	88.5	86.3	87.9	*93*
Precision (%)	82.4	86.7	83.9	85.2	*92.5*
Recall (%)	83.1	87.3	84.5	86.1	*92.9*
F1-Score (%)	82.7	87	84.2	85.6	*92.7*
Processing time (ms)	6.2	5.8	6.5	6.1	*4.5*

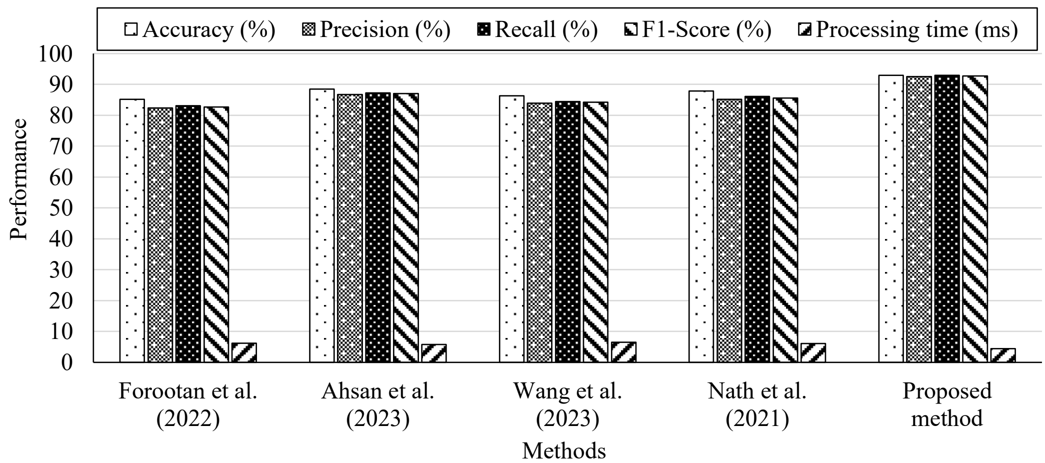

Figure 3. Efficiency analysis of machine defect detection methods based on key performance metrics.

In Figure 3, accuracy, precision, recall, F1-score, and processing time for some machine defect detection techniques are depicted. The proposed method is higher at an accuracy level of 93%, precision at 92.5%, and recall at 92.9% with a score of 92.7% for the F1-score when compared to Forootan et al., Ahsan et al., Wang et al., and Nath et al. whose scores range between 82.7% and 88.5%. Also, if it is compared with the other approaches ranging from 5.8 ms to 6.5 ms, then the proposed method has the shortest processing time of 4.5 ms which ensures scalability and resilience towards industrial real-time applications.

CONCLUSION AND FUTURE ENHANCEMENTS

An excellent technique in a hybrid approach, proved by the efficiency of GRU networks combined with Sugeno fuzzy logic in defect detection of machinery. The system was based on the strength of GRU for its capability in dealing with sequential data analysis and further strength of Sugeno fuzzy logic about dealing with the uncertainty with the fastest processing time was 4.5 ms by giving excellent performances of metrics up to 93% accuracy with 92.5% precision, 92.9% recall, and 92.7% F1-score. This shows how well the system can work under issues that include ambiguous patterns of failure, noisy data, and making quick decisions in fast industrial environments. This system is quite just in terms of scalability and resilience and is much more than ideal for applications in Industry 4.0, allowing for intelligent, flexible, and independent operations. It might improve the model for integrating data of multiple sensors towards an effective detection system, fault in this sense. Furthermore, implementation through cutting-edge optimization strategies like evolutionary algorithms would add to accuracy and computational efficiency as well. It could lead toward improving the capability in real-time by implementation possibilities in a diverse range of industries and implementation at the site of action via edge computing. The proposed system can evolve into a universal, intelligent defect detection framework by addressing these issues that will enhance operational dependability and productivity in several industrial sectors.

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Conflict of Interest

There is no conflict of interests between the authors.

- *Declaration of interests:* 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.
- *Ethics approval:* Not applicable.
- *Permission to reproduce material from other sources:* Yes, you can reproduce.
- *Clinical trial registration:* We have not harmed any human person with our research data collection, which was gathered from an already published article

Authors' Contributions

All authors have made equal contributions to this article.

Author Disclosure Statement

The authors declare that they have no competing interests.

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