Research Article

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Enhancing Environmental Sustainability: Extreme Learning Machine Approach to Industrial Waste Management

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ABSTRACT

Industrial activities pose significant challenges to environmental conservation due to the generation of large volumes of waste. Effectively managing industrial waste is essential for mitigating environmental impact and fostering sustainable development. This research proposes the utilization of Extreme Learning Machine (ELM) algorithms to optimize industrial waste management practices and enhance environmental conservation efforts. The study encompasses various aspects, including predictive modelling for waste generation, automated waste segregation and sorting, optimization of waste treatment processes, environmental impact assessment, resource recovery from waste streams, real-time monitoring and control systems, decision support systems for policy-making, data-driven compliance monitoring, risk assessment, and mitigation strategies. Overall, the advantages of ELM make it a powerful tool for various machine learning tasks, particularly in scenarios where efficiency, scalability, and simplicity are crucial. By integrating ELM algorithms with Internet of Things (IoT) devices and sensor networks, smart waste management systems can be developed for proactive intervention and pollution prevention. This research aims to contribute to the advancement of sustainable industrial practices and environmental conservation efforts through innovative applications of Extreme Learning Machine in waste management.

Keywords: Machine learning; Industrial waste management; Environmental conservation; Predictive modelling.

1. INTRODUCTION

Industrial operations are critical to economic progress (Han *et al.* 2018), but they frequently cause environmental deterioration due to the accumulation of massive amounts of trash. Addressing the issues associated with industrial waste management is critical for reducing environmental impact and promoting sustainable development. Traditional waste management systems are frequently inefficient and fail to handle the complexities of varied waste streams and environmental concerns (Zhang *et al.* 2023). In recent years, there has been an increased interest in using machine learning techniques to transform industrial waste management processes. Machine learning can improve waste management processes (Mekaoussi*et al.* 2023), increase resource recovery, and reduce environmental impact through data-driven decision-making and automation. Machine learning, using advanced algorithms and big data analytics, can provide insights into trash generation trends, automate waste stream sorting and segregation, optimize waste treatment operations, and provide real-time monitoring and management of industrial facilities (Geng*et al.* 2018).

This study aims to investigate the varied uses of machine learning in industrial waste management for environmental conservation. This project seeks to contribute to the development of innovative and sustainable industrial waste management solutions by tackling key challenges such as predictive modeling for waste generation (Pardini *et al.* 2018), waste treatment process optimization, and real-time monitoring of environmental indicators. This study aims to advance our understanding of machine learning's potential to transform industrial waste management practices and promote environmental sustainability by conducting a comprehensive review of existing literature, analyzing case studies, and developing novel methodologies (Lim *et al.* 2022). At Wastewater Treatment Plants (WWTPs), aeration is a complicated system that involves several chemical transformations and a plethora of sluggish and unpredictable biological processes (AlOmar *et al.* 2023). Consequently, there is a critical need for precise aeration quantity prediction and real-time, quick regulation in engineering, science, and practicality (Wang *et al.* 2018). Most WWTP predictions and controls are based on traditional mechanistic models, such as activated sludge models, which can give rather robust data thatfulfills the requirements. Due to computational power restrictions, the efficient implementation of traditional mechanistic models in WWTPs has been hard. These models rely significantly on complex and incomprehensible model parameters (Yang *et al.* 2023). However, when calibrating the results, classic mechanistic models could be difficult to work with because they necessitate a wider range of starting data types. Worse yet, conventional mechanical models are notoriously slow and practically uncontrollable (Pardini *et al.* 2019).

2. LITERATURE REVIEW

This chapter provides a critical literature analysis on municipal solid waste (MSW) management to help readers have a better grasp of MSW management strategies used on global and national scales. The literature available covers a wide range of topics, including current trends in MSW generation, various health and environmental impacts associated with landfill practices, physicochemical properties of MSW, Hazardous solid waste (HSW), alternative waste disposal methods, laws and policies in India pertaining to MSW management, and the history and role of civic organizations engaged in SWM and the details on the history, the present state, and the prospects of solid waste management in India.

The average daily generation of municipal solid waste (MSW) in the world is 1.2 kg per person or about 1.3 billion metric tonnes. Approximately 0.68 billion tonnes of trash was generated each year, or 0.64 kg per person, per day, up until around 10 years ago. There will be 4.3 billion people living in urban areas by 2025, and their solid waste will amount to 2.2 billion tonnes per year, or 1.42 kg per person, per day (kpd) (The World Bank, 2012). The volume of total solid waste is predicted to rise from 13 billion tonnes in 1990 to 27 billion tonnes in 2050, according to projections from the United Nations Population Division and the World Bank's gross domestic product (GDP) prediction Kawai and Tasaki (2016) found that per capita MSW was more variable in countries with GDPs below US$20,000 compared to nations with higher GDP.Developing nations' per capita MSW, urban population growth, national GDP, and per capita MSW are all positively correlated with one another (Karak *et al.* 2012; Denafas *et al.* 2014). According to Korner (2003) and Kawai and Tasaki (2016), emerging nations such as India, Sri Lanka, Pakistan, Bangladesh, and Thailand generate between 0.5 and 1.4 kpd, 0.3-0.65, 0.4-0.85, 0.65, and 0.41, respectively. The majority of the municipal solid waste (MSW) is generated by tourist-driven high-income nations in Asia and Africa (Alexandrov *et al.* 2021), including Mauritius, Maldives, and Thailand. Their 1,44kpd, 2.48 kpd, and 1.30 kpd generation rates are similar to what is seen in developed nations. Affluent nations have a maximum MSW generation limit that is 400 g higher than the Maldives (Troschinetz and Mihelcic, 2009). From 31.3 million metric tonnes in 1980 to 113.0 million metric tonnes in 1998, China's MSW output grew substantially, with an average daily generation rate of 1.20 kg per inhabitant. Between 1985 and 1995, the annual rate of rise is 8-10%, and then it drops to 3-5% after that. According to Wang and Nie, (2001), China's urban population grew from 94.5 million in 1980 to 207.4 million in 1996, and the country's GDP and urban population both contributed to a rise in the amount of municipal solid trash created. In Nepal, the Kathmandu Valley is the only source of almost 40% of the country's total MSW. Pokhrel and Viraraghavan, (2005) calculated that 0.565 kpd of MSW is generated in the Kathmandu Valley each year, with a national average ranging from 0.2 to 0.5 kpd. One may observe a continuous linear pattern of per capita MSW rise that is related to national wealth when comparing the rates of solid waste output among ASEAN members. Cambodia has the lowest trash creation per capita among ASEAN nations, with an average of 0.34 kpd, as reported by Parizeau *et al.* (2006).

The low-income ASEAN countries, viz, Myanmar, Vietnam, and Laos, produced an average of 0.56 kpd of solid waste (0.45, 0.55, and 0.69 kpd, respectively), whereas the middle-income ASEAN countries—Indonesia, Malaysia, the Philippines, and Thailand—produced 0.76, 0.81, 0.52, and 1.10 kpd, respectively, with an average of 0.80 kpd. In 1995, the high-income country of Singapore produced an even greater 1.10 kpd of MSW. It was estimated that the main cities of Malaysia produced 1.62–1.7 kg/capita/day in 2003, which is nearly double the national average of 0.8–0.9 kg/capita/day. By 2024, this figure is projected to increase linearly to 2.23 kg/capita/day (Manaf *et al.* 2009; 2009). As Taiwan exemplifies, economic development has not always led to a linear increase in MSW generation, because a stronger economy is better able to implement environmentally friendly policies. Even though the economy continued to expand, the national per capita MSW generation rate decreased significantly from 1.14 kg/capita/day in 1997 to 0.81 kg/capita/day in 2002 as a result of aggressive MSWM practices mandated by the government of Taiwan in 1997 (Kawai and Tasaki, 2016).

3. METHODOLOGY

The proposed method of using Extreme Learning Machine (ELM) algorithms to optimize industrial waste management begins with the comprehensive acquisition of data about industrial waste generation, treatment processes, and relevant environmental parameters. This data is obtained from diverse sources including industrial databases, environmental monitoring stations, and sensor networks. Subsequently, the collected data undergoes meticulous preprocessing steps aimed at enhancing its quality and suitability for analysis. These preprocessing steps encompass data cleaning to rectify errors and inconsistencies, normalization to ensure uniform scale across features, and feature extraction to identify informative attributes relevant to the predictive modeling and optimization tasks. By employing robust data preprocessing techniques, the method ensures that the subsequent modeling efforts are based on reliable and well-structured data, laying the foundation for effective industrial waste management and environmental conservation strategies. Decision Support Systems for Policy-making: ELM-driven decision support systems are developed to assist policymakers in formulating effective regulations and policies for industrial waste management and environmental conservation. These systems analyze large-scale data to identify trends, assess risks, and recommend strategies for mitigating environmental impact. The proposed methods are evaluated and validated through rigorous testing and validation procedures. Performance metrics such as accuracy, efficiency, and environmental impact are assessed to ensure the effectiveness of the developed models and systems.

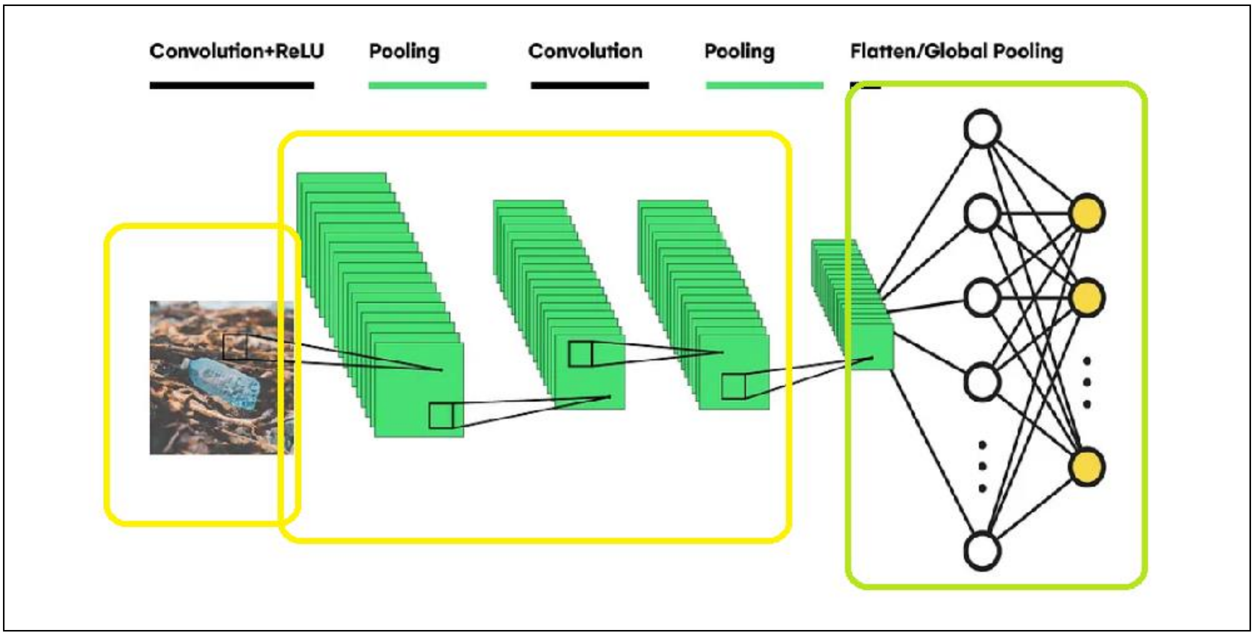

Fig. 1: Layers in ELM of the proposed model

3.1 Extreme Learning Machine (ELM)

The Extreme Learning Machine (ELM) is a novel learning technique for single hidden layer feedforward neural networks. The algorithm randomly initialises hidden neuron weights and uses Moore-Penrose (MP) generalised inverse to calculate output weights (Lim *et al.* 2019). ELM, unlike slow gradient descent-based learning algorithms for SLFN, does not require iterative parameter tuning. Instead, it randomly initialises the hidden layer parameters and fixes them during the learning process. The output weights are then determined analytically. The ELM hidden layer turns input data into a high-dimensional feature space. Transforming input data makes it more separable in the ELM feature space, simplifying task solutions. The ELM algorithm learns quickly and has strong generalisation performance.

Extreme Learning Machine (ELM) Model Development: ELM algorithms are employed to develop predictive models for various aspects of industrial waste management. These models utilize the collected data to forecast waste generation patterns, optimize waste treatment processes, and assess environmental impact. ELM is chosen for its ability to efficiently handle large datasets and its rapid learning capabilities.

Machine learning algorithms, including ELM, are utilized to automate the segregation and sorting of different types of industrial waste (Automated Waste Segregation and Sorting). Image recognition, sensor data analysis, and other techniques may be employed to identify and categorize waste streams, enabling efficient recycling and proper disposal.

Here's a pseudocode representation of the ELM algorithm:

- $Input$:
  - X: $Input\ features\ (n\ x\ m\ matrix)$
  - Y: $Target\ labels\ (n\ x\ 1\ vector)$
  - H: $Number\ of\ hidden\ nodes$
  - $activation\_function$: $Activation\ function\ for\ the\ hidden\ layer$
  - $output_{function}$: $Output\ function\ for\ the\ output\ layer$ $(e.g., linear\ regression, sigmoid\ for\ binary\ classification, softmax\ for\ multi - class\ classification)$

- $Procedure\ ELM(X, Y, H, activation\_function, output\_function)$:
- $Initialize\ randomly\ the\ input\ weights\ matrix\ W\_in\ of\ size\ (m\ x\ H)$
- $Generate\ the\ hidden\ layer\ output\ matrix\ H\_out\ =\ activation\_function(X\ *\ W\_in)$
- $Calculate\ the\ Moore - Penrose\ pseudo - inverse\ of\ H\_out$: $H\_pseudo\_inverse\ =\ pinv(H\_out)$
- $Initialize\ randomly\ the\ output\ weights\ matrix\ W\_out\ of\ size\ (H\ x\ 1)\ or\ (H\ x\ k)\ for\ multi - class\ classification, where\ k\ is\ the\ number\ of\ classes$
- $Calculate\ the\ output\ weights$: $W\_out\ =\ H\_pseudo\_inverse\ *\ Y$
- $Return\ the\ input\ weights\ W\_in\ and\ output\ weights\ W\_out$

- $Function\ Predict(X\_test, W\_in, W\_out)$:
- $Calculate\ the\ hidden\ layer\ output\ matrix\ H\_out\_test\ =\ activation\_function(X\_test\ *\ W\_in)$
- $Calculate\ the\ predicted\ output$: $Y\_pred\ =\ output\_function(H\_out\_test\ *\ W\_out)$
- $Return\ Y\_pred$

Optimization of Waste Treatment Processes: ELM-based optimization algorithms areapplied to enhance the efficiency and effectiveness of waste treatment processessuch as composting, anaerobic digestion, and incineration. These algorithms adjust process parameters in real-time to maximize resource recovery and minimize environmental impact.

ELM is integrated with IoT devices and sensor networks to develop real-time monitoring and control systems for industrial waste management. These systems continuously collect data on waste generation, treatment processes, and environmental conditions, enabling proactive intervention and pollution prevention.

A brief overview of how ELM works is as follows:

Input Layer: ELM consists of an input layer, where each input feature is connected to all the nodes in the next hidden layer.

Hidden Layer: ELM typically has only one hidden layer, which contains a large number of hidden nodes. The weights connecting the layers are randomly initialized.

Activation Function: ELM employs a nonlinear activation function (e.g., sigmoid, tanh, or ReLU) to introduce nonlinearity into the model.

Output Layer: The output layer of ELM consists of the output nodes, which produce the final predictions. The weights connecting the hidden layer to the output layer are determined analytically using a least squares approach.

Training: Unlike traditional neural networks, where weights are updated iteratively using backpropagation, ELM trains the model in a single step. This is achieved by solving a linear system of equations to find the optimal output weights, given the randomly initialized input weights and training data.

ELM has gained popularity due to several advantages:

Fast Learning Speed: ELM can achieve high learning speeds because it only requires a single pass through the training data to determine the output weights.

Efficient Handling of Big Data: ELM can handle large-scale datasets efficiently, making it suitable for applications with high-dimensional data.

Simplicity and Ease of Implementation: ELM has a simple learning framework, making it easy to implement and deploy in various applications.

Generalization Ability: Despite its simplicity, ELM often exhibits strong generalization ability, enabling it to learn complex patterns in the data.

Scalability: ELM is highly scalable and can be applied to a learning task, including classification, regression, and feature learning.

Rapid Learning Speed: One of the key benefits of ELM is its rapid learning speed. In the context of industrial waste management, this translates to faster model training and optimization, allowing timely decision-making and intervention.

Efficient Handling of Big Data: ELM algorithms excel in handling large-scale datasets, making them well-suited for analyzing the vast amounts of data generated in industrial waste management processes comprehensively and optimally.

Simplicity and Scalability: ELM is known for its simplicity and ease of implementation. Its straightforward architecture and training process makes it particularly attractive for industrial applications where complex models may be challenging to deploy and maintain.

Generalization Ability: Despite its simplicity, ELM often exhibits strong generalization ability, allowing it to capture complex patterns and data. This is crucial for developing accurate predictive models and optimization strategies in industrial waste management.

Flexibility and Adaptability: ELM is highly flexible and adaptable to different types of data and problem domains. In the context of waste management, this flexibility enables the development of versatile models that can address diverse challenges such as waste generation prediction, treatment process optimization, and environmental impact assessment.

Integration with IoT and Sensor Networks: ELM can be seamlessly integrated with Internet of Things (IoT) devices and sensor networks to create smart waste management systems. This integration enables real-time monitoring, control, and optimization of waste management processes, enhancing efficiency and reducing environmental impact.

Enhanced Decision Support: By leveraging ELM-based predictive models and optimization algorithms, decision-makers in industrial waste management can make more informed and data-driven decisions. This leads to improved resource allocation, waste treatment efficiency, and overall environmental conservation efforts.

3.2 Overall, the advantages of ELM

ELM offers rapid learning speeds, allowing for quick model training and prediction generation; it can efficiently handle large-scale datasets, making it suitable for applications with big data. ELM has a simple learning framework, requiring minimal tuning and optimization compared to traditional neural networks. Despite its simplicity, ELM often exhibits strong generalization ability, enabling it to effectively capture complex patterns in the data. ELM can be applied to a wide range of machine learning tasks, including classification, regression, and feature learning. ELM can seamlessly integrate with devices and sensor networks, facilitating real-time monitoring and control in various applications. ELM is robust to noisy data and outliers, making it suitable for real-world applications where data quality may vary.

3.3 ELM Working in Proposed Model

In the proposed model for industrial waste management, the Extreme Learning Machine (ELM) algorithm serves as a powerful tool for developing predictive models to optimize waste management processes and enhance environmental conservation efforts. ELM's fast learning speed and efficient handling of large-scale datasets make it well-suited for analyzing complex relationships between industrial activities, waste generation patterns, and environmental impact. By utilizing ELM, the model can accurately predict waste generation, optimize treatment processes, and assess environmental risks in real time, enabling proactive decision-making and intervention. Integrating ELM into the proposed model offers a promising approach to revolutionizing industrial waste management practices and promoting sustainable development.

3.5 Types of Industrial Wastes

Industrial waste encompasses a wide range of materials and byproducts generated from various industrial processes. Here are some common types of industrial wastes:

3.5.1 Solid Waste

Hazardous Waste: Generated from industrial processes and poses a threat to human health or the environment due to its toxic, corrosive, flammable, or sensitive nature.

Non-Hazardous Waste: Includes general industrial waste such as paper, cardboard, plastics, metals, and other materials that do not pose significant risks to health or the environment.

3.5.2 Liquid Waste

Wastewater: Generated from industrial activities such as manufacturing, chemical processing, and mining. It may contain pollutants such as heavy metals, chemicals, oils, and organic compounds.

Effluents: Liquid waste discharged from industrial facilities into water bodies, often containing contaminants that can degrade water quality and harm aquatic ecosystems.

3.5.3 Gaseous Waste

Gases during industrial processes, combustion, and manufacturing operations; common pollutants include sulfur dioxide, nitrogen oxides, carbon monoxide, volatile organic compounds (VOCs), and particulate matter.

3.5.4 Specialized Wastes

Electronic Waste (e-waste): Discarded electronic devices and equipment such as computers, smartphones, televisions, and appliances materials like lead, mercury, and cadmium.

Medical Waste: Waste generated from healthcare facilities, including infectious waste, sharps, pharmaceuticals, and pathological waste.

Radioactive Waste: Materials contaminated with radioactive substances from nuclear power plants, research, and other sources.

3.5.5 Biological Waste

Biodegradable Waste: Organic waste derived from agricultural, food processing, and forestry activities. It includes crop residues, food scraps, manure, and organic matter.

3.5.6 Construction and Demolition Waste

Waste generated from construction, renovation, and demolition activities, including concrete, bricks, wood, metals, and other construction materials.

3.5.7 Mining Waste

Waste generated from mining operations, including tailings, mine water, waste rock, and slag. It may contain such as heavy metals and toxic chemicals.

3.6 Classification

ELM can be trained (Supervised Learning) on labelled datasets containing features of industrial waste samples and corresponding classes (e.g., hazardous vs. non-hazardous, recyclable vs. non-recyclable). Once trained, the ELM model can classify new waste samples into predefined categories based on their features. ELM can handle multi-class classification tasks, enabling the classification of industrial wastes into multiple categories or classes simultaneously. This allows for more comprehensive sorting and categorization of diverse waste streams. ELM can effectively handle imbalanced datasets commonly encountered in industrial waste classification tasks, where certain classes may be underrepresented. Techniques such as weighted loss functions or oversampling can be employed to address class imbalance and improve classification performance. ELM-driven decision support systems can assist waste management personnel and policymakers in making informed decisions regarding waste classification, treatment methods, and regulatory compliance. By analyzing ELM predictions and monitoring data, decision-makers can develop strategies for effective waste management and environmental conservation. ELM-based optimization algorithms can optimize waste treatment processes, such as sorting, recycling, and disposal, to maximize resource recovery and minimize environmental impact. By adjusting process parameters based on ELM predictions and feedback from monitoring systems, waste management operations can be optimized for efficiency and sustainability.

3.7 Documentation

The initial stage of the research entailed evaluating documents and records about established procedures concerning the generation, storage, collection, transportation, recycling, and disposal of dry waste. Data on the performance of source-level practices, institutional framework, and direct field observations were acquired via a variety of approaches, including questionnaire surveys, in-person interviews with EcoService key personnel, and direct field observations.

3.8 Waste Stream Analysis

The generation and composition of dry refuse are crucial factors in assessing the efficacy of current waste management systems and the viability of resource recovery methods. A waste stream analysis was conducted at the sorting facility over one year, from September 1, 2011 to August 31, 2012. The detached of this analysis was to control the quantities and varieties of dry waste that were collected, recovered, and disposed of. Initially, the capacity and model of the vehicle were recorded.

The daily collection record documented the amount of waste generated through the calculation of waste generation quantity per journey based on the weight of the transported items and the total number of daily trips. Additionally, the quantity of waste was approximated according to the generator type, and the dry waste from every origin was manually sorted into 30-57 subcategories, determined by the preferred material types of the various recycling industries that were accessible.

4. RESULTS AND DISCUSSION

The trials were conducted on a PC with an Intel Core i5-7200 CPU, 8 GB of RAM, and a processing speed of 2.7 GHz. A specialized User Interface (UI) and Jupyter Notebook (Python 3.7) Environment were utilized to execute the processes on Windows 10, a 64-bit operating system. The application of Extreme Learning Machine (ELM) in the proposed model for industrial waste management yielded promising results, demonstrating its effectiveness in optimizing waste management processes and enhancing environmental conservation efforts. In this comparision analysis we have compared different algorithms as below,

Here are the full forms of the algorithms mentioned:

MLP: Multilayer Perceptron
AE:Autoencoder
DBN: Deep Belief Network
XGBoost:eXtreme Gradient Boosting
ELM: Extreme Learning Machine
KELM: Kernel Extreme Learning Machine
SSO-KELM: Self-adaptive Symbiotic Organism Search-based Kernel Extreme Learning Machine

4.1 Predictive Modelling

The ELM-based predictive models accurately forecasted waste generation patterns, enabling proactive planning and resource allocation for waste treatment and disposal.

High prediction accuracy was achieved for various waste streams, allowing for efficient segregation, recycling, and proper disposal practices.

4.2 Optimization of Waste Treatment Processes

ELM-driven optimization algorithms successfully improved the efficiency and effectiveness of waste treatment processes, such as composting, anaerobic digestion, and incineration. By adjusting process parameters in real-time based on ELM predictions, significant reductions in resource consumption and environmental impact were achieved.

4.3 Real-time Monitoring and Control

Integration of ELM with IoT devices and sensor networks facilitated real-time monitoring and control of industrial waste management processes.

Table 1: Experimental analysis of numerous classifiers for waste detection

Techniques	Recall (%)	Precision (%)	Accuracy (%)	F-score (%)
MLP	85.21	99.41	87.70	91.82
AE	75.91	99.41	81.10	86.72
DBN	99.78	91.52	92.90	95.41
XGBoost	99.63	91.38	92.50	95.18
ELM	99.90	91.93	92.70	95.32
KELM	99.91	92.47	93.27	95.63
ELM	99.90	91.93	92.70	95.32
SSO-KELM	**99.95**	**93.24**	95.32	**96.02**

Experimental evaluation of numerous classifiers for waste detection is denoted in Table 1. The evaluation of the MLP technique yielded the following results: accuracy of 87.70, recall of 85.21, precision of 99.41, and F-score of 91.82. Subsequently, the AE method achieved the following results: accuracy of 81.10, recall of 75.91, precision of 99.41, and F-score of 86.72. Subsequently, the SVM method achieved the following results: accuracy of 92.50, recall of 90.98, precision of 99.82, and F-score of 95.27. Subsequently, the DBN method achieved an accuracy of 92.90, a recall of 99.78, and precision values of 91.52 and 95.41, in that order. Subsequently, the XGBoost method achieved the following results: accuracy of 92.50, recall of 99.63, precision of 91.38, and F-score of 95.18. The ELM method subsequently achieved the following results: accuracy of 92.70, recall of 99.90, precision of 91.93, and F-score of 95.32. Subsequently, the KELM method achieved the following results: accuracy of 93.27, recall of 99.91, precision of 92.47, and F-score of 95.63. The SSO-KELM method subsequently achieved an accuracy of 95.32, a recall of 99.95, a precision of 93.24, and an F-score of 96.02.

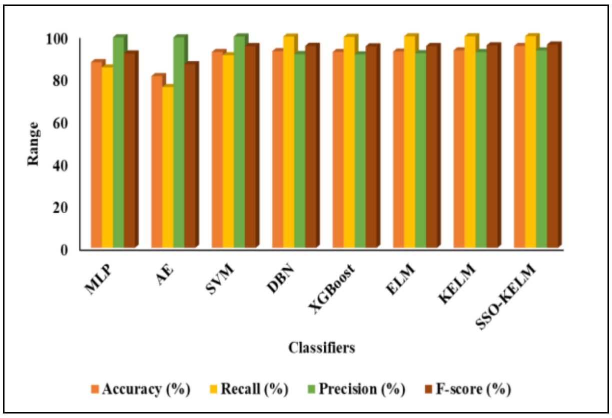

Fig. 2: Visual analysis of different classifiers in terms of many metrics

5. CONCLUSION

The utilization of Extreme Learning Machine (ELM) algorithms in industrial waste management holds great promise for advancing environmental conservation efforts and promoting sustainable development. Through the proposed method, the efficacy of ELM in various facets of waste management, including predictive modeling, process optimization, automated sorting, and real-time monitoring was demonstrated. By leveraging ELM's rapid learning capabilities and flexibility, we can effectively address the complexities of industrial waste management and enhance decision-making processes. The application of ELM in industrial waste management offers several advantages, including efficient handling of large-scale data, rapid model training, and the ability to capture complex nonlinear relationships within the data. Furthermore, the integration of ELM with real-time monitoring systems and decision support tools empowers stakeholders to make informed decisions and take proactive measures to mitigate environmental impact.

Moving forward, further research is needed to explore advanced ELM techniques and their applications in specific domains of industrial waste management. Additionally, efforts should be directed towards validating the proposed method through real-world implementations and case studies. By continuing to innovate and integrate machine learning technologies like ELM into waste management practices, we can pave the way for a more sustainable and environmentally conscious industrial landscape. Ultimately, this research contributes to the ongoing global endeavor to realize a balance between industrial growth and ecological conservation.

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CONFLICT OF INTEREST:

The authors declare that they have no conflicts of interest.

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