Applied Chemical Engineering (2026) Volume 9 Issue 1 ISSN: 2578-2010 (O)
doi: 10.59429/ace.v9i1.5879

ORIGINAL RESEARCH ARTICLE

Deep Learning for Real-Time Detection of Pollutants in Bio-Energy Production and Utilization Systems

Hemlata Suresh Gaikwad[1], Nidhi Sharma[2], Shital Y. Solanke[3], Swati Mukesh Dixit[4,6], Anant Sidhappa Kurhade[5,6*]

[1] *Department of Information Technology, PCET's Pimpri Chinchwad College of Engineering and Research, Ravet, Pune — 412101, Maharashtra, India.*

[2] *Department of Applied Sciences and Engineering, AISSM's Institute of Information Technology, Pune — 411001, Maharashtra, India.*

[3] *Department of Mathematics, School of Science and Humanities, Ramdeobaba University, Ramdeobaba tekdi, Katol road, Nagpur — 440013, Maharashtra, India.*

[4] *Department of Electronics and Telecommunication Engineering, Dr. D. Y. Patil Institute of Technology, Pimpri, Pune, 411018, Maharashtra, India.*

[5] *Department of Mechanical Engineering, Dr. D. Y. Patil Institute of Technology, Sant Tukaram Nagar, Pimpri, Pune — 411018, Maharashtra, India.*

[6] *Dnyaan Prasad Global University (DPGU), School of Technology and Research, Dr. D. Y. Patil Unitech Society, Sant Tukaram Nagar, Pimpri, Pune — 411018, Maharashtra, India*

***Corresponding author:** Anant Sidhappa Kurhade, a.kurhade@gmail.com

ARTICLE INFO

Received: 7 January 2026
Accepted: 11 February 2025
Available online: 03 March 2026

ABSTRACT

Bio-energy facilities are critical aspects of sustainability and low-carbon energy transitions, even though emitting pollutants from the combustion of biomass materials, anaerobic fermentation, and biofuel use is a serious environmental issue. Efficient real-time monitoring is the necessary requirement to maintain a clean energy production, satisfy regulations and care human's health. In most previous works, traditional monitoring methods are used which demonstrate obvious disadvantage with slow response time and poor flexibility of operation and unsatisfactory detection performance in a dynamic state; therefore, creating a gap that will only improve with further research for the intelligent in-situ pollution detecting application. The purpose of this project is to explore the use of deep learning to the real-time detection and monitoring of pollutants in bio-energy production/consumption systems. A comprehensive methodology is used to combine multi-sensor measurements of gas concentration, process parameters, and temporal response with state-of-the-art deep learning methods including convolutional and recurrent neural networks. The results suggest that the deep learning-based models provide remarkably high detection accuracy, efficiency and robustness compared to conventional approaches, leading to an earlier abnormal emission pattern detecting process. These findings indicated that intelligent monitoring system can help to achieve the optimized process control, emission reduction and predictive maintenance in bio-energy plant. Practical implications This work contributes directly to Sustainable Development Goals, namely SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation and Infrastructure), SDG 12 (Responsible Consumption

and Production) and SDG 13 (Climate Action) by supporting cleaner bio-energy operations, environmental friendliness and sustainable industrial development.
Keywords: Deep learning; Bio-energy systems; Real-time pollutant detection; Emission monitoring; Sustainable Development Goals (SDGs)

1. Introduction

Bio-energy is one of the critical renewable energy sources, which uses organic materials (agricultural residues; forest biomass, output from biogas and biofuel) for electricity and/or heat production in the global market. Although bio-energy is renewable, its production processes can produce air pollutants if not properly managed. Hence, continuous monitoring of pollutants is imperative for the environmental consciousness and system effectiveness, along with human life security. Deep learning technologies serve as an enabling analytical framework to address the demand in environmental monitoring and data interpretation. In particular, deep learning that is a subfield of machine learning (ML), has great power in capturing complex features upon large-scale environmental datasets and it becomes the "game-changer" for understanding convoluted Earth systems and adapting to environmental changes [1]. This allows better predictions and on-line monitoring of diverse environmental factors such as the quality of air and water [2, 3]. These are of significant relevance for bio-energy systems and particularly when considering the dynamic nature of pollutant generation, there is a need to have advanced automatic monitoring tools [1,4]. This paper systematically introduces the current progress about using deep leaning technology and it's related to realize rapid pollutant monitoring (mainly focuses bio-energy production and utilization system) under complicated environment. The incorporation of artificial intelligence, especially deep learning, allows for automated data gathering and real-time analysis as well as predictive model development that can alleviate the restrictions posed by conventional monitoring techniques in bioenergy systems [3, 5]. Such advanced methodologies support quick reaction against environmental threats and enhance decision-making on sustainable remediation actions [6]. The use of deep learning models, such as convolutional neural networks, recurrent neural networks and transformers, facilitates complex analysis of sensor-based environmental data and industrial parameters at large scale predicting pollutant level accurately and anomaly detection [4]. Additionally, hybrid models based on deep learning algorithm that ensembles the individual strengths of different models have advanced the predictive capability and generalization performance for proactive management of environment [4]. Such flexibility is extremely important to bio-energy processes that tend to be variable with respect to feedstock quality and operating condition which directly affect the pollutant emission [7].

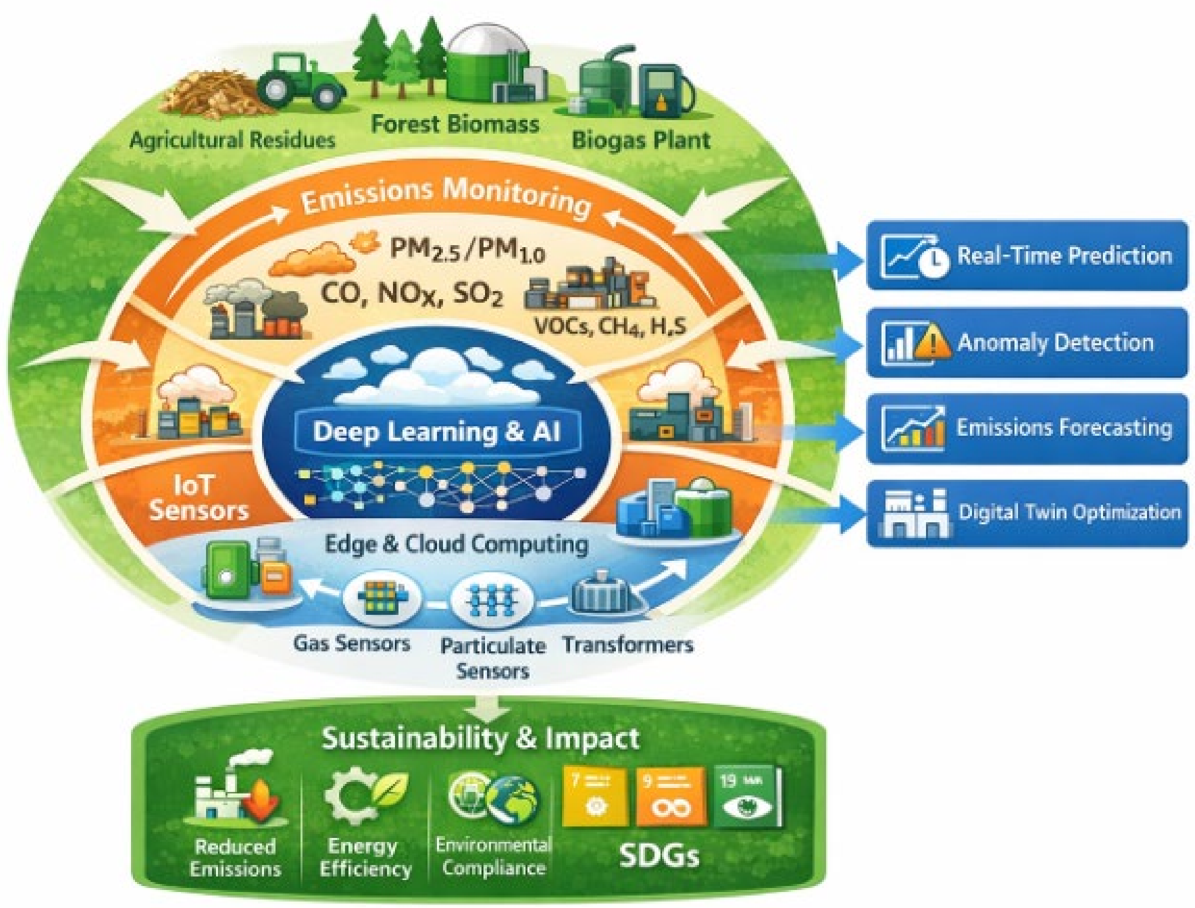

Figure 1. Deep Learning–Driven Intelligent Framework for Real-Time Pollutant Monitoring in Bio-Energy Systems

This **figure 1** illustrates an integrated framework where IoT sensors continuously monitor pollutant emissions across bio-energy production and utilization processes. The collected data are analyzed using advanced deep learning models to enable real-time prediction, anomaly detection, and emission forecasting. The framework supports sustainable bio-energy operation by improving environmental compliance, operational efficiency, and alignment with Sustainable Development Goals. This review focuses on the different deep learning methodologies for bio-energy systems, critically evaluating their performance in real-time pollutant characterizations and describing potential study cases to maximize their utilization [4, 8]. This includes the investigation into the deployment of Internet of Things sensors for acquiring rich data, combined with cloud computing for real-time data processing, as well as boosting interpretability with explainable AI methods in industrial environments [4]. Finally, this in-depth review addresses how deep learning can help improve the sustainability and operational efficiency of bio-energy systems by improving robustness and enabling real-time monitoring for pollutant detection within the environmental protection framework [9]. The conversation will then address the fundamental principles underpinning deep learning in relation to pollutant detection and provide a complementary detailed treatment on specific model architectures and their respective application within a range of bio-energy arenas. This involves overcoming considerations such as data heterogeneity, model interpretability and building reliable real-time deployment techniques [4,10]. In addition, the review will show how DL is supporting the sustainable development goals through allowing cleaner energy generation and reducing potential environmental problems connected with bioenergy conversion processes [10]. It will also address the policy implications, stressing how advanced detection can inform tighter environmental standards and reduce compliance burden. The knowledge extracted from the deep learning models can further be used to guide predictive EIA for optimization of greener and more efficient set ups in industries [4]. This sort of cooperation will be a necessity in the creation of self-adaptive systems that are more adaptable to economics as well as social values, to get closer toward the intelligent manufacturing systems where interconnected machines and sensor networks support real-time communication and automation [11].

The traditional monitoring of pollutants has been carried out mainly through a laboratory analysis or rule-based sensors that are usually slow and cannot be used under variable operating conditions. Deep learning, which is a subset of AI research, proved to be an effective candidate as it can handle large quantities of complicated data and detect non-linear relationships. With the development of deep learning, it is impossible to achieve real-time detection for pollutants in bio-energy systems through sensor networks and industrial control system. This transformative potential is important for contributing towards several Sustainable Development Goals by improving resource utilization, energy efficiency and reducing environmental footprint in industrial processes [12, 13]. Deep learning models have succeeded in online and efficient processing of the monitoring data, which supports timely detection of anomalies and the prompt implementation of protective measures to protect environmental safety as well as economic interests [14]. Additionally, these sophisticated diagnostic capabilities allow for proactive maintenance and plant tuning to minimize overall downtime as well as maximize energy conversion efficiency. Moreover, machine learning for bioenergy is not limited to real-time monitoring but it also includes prediction of enough energy consumption and carbon emission pattern that helps industry take proactive action in preventing environmental issues [4, 7, 15]. The addition of digital twins to those AI-controlled systems further optimizes and improves control in smart bio refineries, as a result improving efficiency and profitability [16]. This additional integration enables a circular bio economy by lowering waste and emissions and improving energy self-sufficiency as well [16]. Such a combined application of AI, IoT, and digital twin technologies has set up an effective infrastructure for intelligent manufacturing systems that can make industries environmentally friendly and growth sustainable in nature [17]. These modern systems, beneficial as they may be, are faced with challenges in terms of the privacy and security of data; computational requirements, as well as the need for robust validation mechanisms to guarantee safe and trustworthy autonomous decision-making [18]. In order to tackle these challenges, a multi-disciplinary collaboration among the pertinent parties must be created to enable energy innovations in line with sustainability objectives and develop complete regulatory frameworks [19]. Deep learning approaches are increasingly being used in a broad range of fields, including the biofuels industry, to improve process efficiency and reduce environmental impact [20].

Table 1. Deep Learning–Based Pollutant Monitoring in Bio-Energy Systems

Aspect	Description	Relevance to Bio-Energy Systems
Bio-energy sources	Energy derived from organic materials such as agricultural residues, forest biomass, biogas, and biofuels	Provides renewable electricity and heat but generates dynamic pollutant emissions depending on feedstock and operating conditions
Pollutant generation issue	Emission of air pollutants during bio-energy production if processes are not properly managed	Requires continuous, accurate, and real-time monitoring to ensure environmental safety and compliance
Traditional monitoring methods	Laboratory analysis and rule-based sensors with slow response and limited adaptability	Ineffective under variable operating conditions and unsuitable for real-time decision-making
Deep learning (DL)	Subfield of machine learning capable of learning complex non-linear patterns from large datasets	Enables accurate prediction, anomaly detection, and real-time pollutant characterization
DL model architectures	CNNs, RNNs, Transformers, and hybrid models	Capture spatial–temporal features of sensor data and improve prediction accuracy
Hybrid DL models	Ensemble approaches combining multiple DL models	Enhance robustness and adaptability to feedstock and operational variability
IoT sensor integration	Networked sensors continuously collect environmental and industrial data	Provides high-resolution real-time data streams for monitoring

Aspect	Description	Relevance to Bio-Energy Systems
Cloud computing	Centralized platforms for large-scale data processing and storage	Enables scalable real-time analytics and DL deployment
Real-time monitoring & prediction	Continuous pollutant estimation, forecasting, and anomaly detection	Supports rapid response to environmental risks and operational optimization
Explainable AI (XAI)	Methods that improve transparency and interpretability of DL models	Builds trust and facilitates industrial adoption
Digital twins	Virtual replicas of bio-energy systems integrated with AI	Optimize control strategies and reduce emissions
Sustainability impact	Improved resource efficiency and emission reduction	Supports Sustainable Development Goals and circular bio-economy
Policy and regulation	AI-driven monitoring informs environmental standards and compliance	Reduces compliance burden and supports predictive EIA
Challenges	Data heterogeneity, privacy, computational cost, and validation issues	Limits large-scale deployment without multidisciplinary collaboration
Future outlook	Integration of AI, IoT, DL, and intelligent manufacturing	Enables self-adaptive, sustainable bio-energy industries

Table 1. (*Continued*)

Table 1 summarizes the role of deep learning–based frameworks in real-time pollutant monitoring for bio-energy systems, highlighting key technologies, models, and system components. It also outlines their environmental benefits, sustainability impact, and associated challenges in achieving efficient and compliant bio-energy operations.

Bio-energy systems, though renewable, generate dynamic and process-dependent pollutant emissions. Conventional monitoring methods lack real-time capability, adaptability, and accuracy under varying operating conditions, limiting early detection and effective emission control. This study aims to apply deep learning–based models for real-time detection and monitoring of pollutants in bio-energy production and utilization systems, enabling accurate emission prediction, early anomaly identification, and improved environmental compliance.

2. Pollutant Emissions in Bio-Energy Systems

Bio-energy production and utilization encompass a range of conversion technologies; each associated with specific pollutant emission pathways across different operational stages. During **biomass combustion**, the incomplete oxidation of organic matter leads to the emission of particulate matter ($PM_{2.5}$ and PM_{10}), which poses serious respiratory and cardiovascular health risks. In addition, gaseous pollutants such as carbon monoxide (CO), nitrogen oxides (NO_x), and sulphur dioxide (SO_2) are released depending on combustion efficiency, fuel sulphur content, and air–fuel mixing conditions. These emissions contribute to local air pollution, smog formation, and acid rain. Furthermore, the thermochemical conversion of lignocellulosic biomass, while offering a renewable carbon source for biofuels, presents challenges in accurately quantifying renewable carbon content due to complex process dynamics, often requiring advanced AI-aided approaches for real-time tracking [21]. Similarly, anaerobic digestion and fermentation processes, while generating biogas and other bio-products, can release volatile organic compounds and methane, a potent greenhouse gas, if not properly managed [22]. Beyond these direct emissions, the broader life cycle of bioenergy systems, including biomass cultivation, transport, and processing, can also contribute to environmental burdens such as eutrophication from fertilizer runoff or land-use change impacts [16]. The **figure 2** diverse biomass feedstocks to specific conversion technologies and their distinct pollutant profiles, ranging from particulate matter and methane to complex tars. It illustrates the critical role of AI and deep learning in real-time monitoring to detect these emissions and ensure environmental compliance.

In **biogas and anaerobic digestion systems**, emissions mainly arise from gas leakage and by-product formation. Methane leaks are of particular concern due to their high global warming potential. Hydrogen sulphide (H_2S), a toxic and corrosive gas, is commonly present in raw biogas and can damage equipment if not properly removed. Ammonia emissions may also occur, especially when nitrogen-rich feedstocks such as animal manure are used, leading to odor issues and secondary particulate formation. These diverse pollutant streams necessitate a comprehensive understanding of bioenergy conversion pathways to implement targeted monitoring and mitigation strategies effectively [23]. Moreover, the variability in biomass feedstocks and operational parameters further complicates emission profiles, necessitating real-time monitoring to capture these fluctuations accurately [24].

Biofuel production and utilization processes, including fermentation, transesterification, and fuel handling, can release volatile organic compounds (VOCs) and aldehydes. These compounds contribute to photochemical ozone formation and may have adverse health effects upon prolonged exposure. Emissions are often influenced by process control, solvent use, and storage conditions. Conversely, while some biomass conversion processes yield greenhouse gas emissions, these are generally lower than those from fossil fuels, contributing to the substantial environmental benefits of renewables [25]. Nevertheless, the complexities of bioenergy systems, involving numerous interconnected processes and diverse pollutant sources, necessitate sophisticated monitoring and prediction models [26, 27]. Therefore, advanced deep learning approaches become indispensable for discerning intricate patterns within vast datasets generated by these systems, enabling precise pollutant identification and quantification in real-time [28]. This becomes particularly crucial for understanding the occurrence, fate, and toxicological interactions of contaminants, which is vital for minimizing the environmental impact of centralized bio economy systems [29]. This is especially pertinent as biogas production itself can introduce airborne contaminants such as micro plastics, carbonyl compounds, and ammonia, which is often overlooked in environmental impact assessments [29].

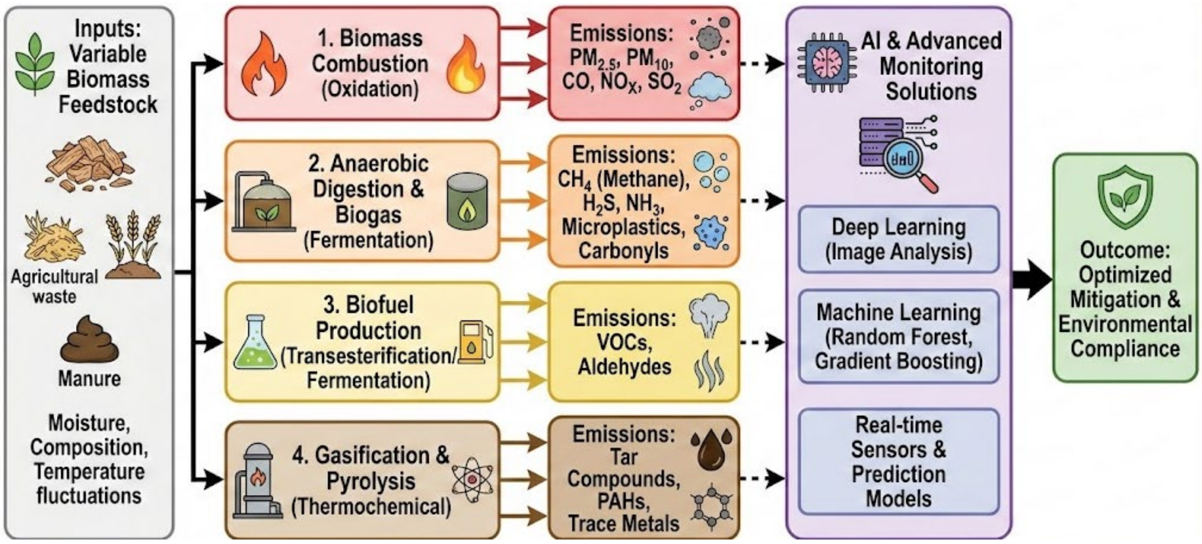

Figure 2. Pollutant Emission Pathways and AI-Integrated Monitoring in Bio-Energy Systems

In **gasification and pyrolysis units**, high-temperature thermochemical reactions generate complex pollutants such as tar compounds, polycyclic aromatic hydrocarbons (PAHs), and trace metals. These pollutants can foul downstream equipment and pose environmental hazards if released untreated. The diverse and dynamic nature of these pollutants underscores the critical need for sophisticated, real-time detection systems to ensure both operational efficiency and environmental compliance. Therefore, deep learning techniques, particularly that leveraging image analysis, offer a promising avenue for monitoring complex combustion processes and predicting emission levels from bio-energy systems with high accuracy [30, 31]. Furthermore, machine learning algorithms, including Random Forest and gradient boosting, have demonstrated efficacy in predicting the presence of nitrogen heterocycles in bio-oil, which are critical precursors for NOx emissions [32]. The monitoring and prediction of nitrogen oxides emissions from biomass combustion remain a significant concern in the power generation industry, emphasizing the need for robust real-time techniques to meet stringent environmental regulations [33].

Overall, pollutant concentration and composition in bio-energy systems are highly dynamic, varying with feedstock characteristics, moisture content, operating temperature, and system load. This variability underscores the necessity for real-time, adaptive monitoring and control strategies to ensure environmental compliance and sustainable operation.

3. Role of Deep Learning in Real-Time Pollutant Detection

Deep learning (DL) is attractive as a tool for real-time pollutant detection in bio-energy production and utilization systems, since it can learn complex, nonlinear relationship between different process variables. In contrast to traditional rule-based and statistical approaches, DL models are capable of learning hierarchical features from raw (or minimal pre-processed) sensor data in an automated manner, which results in more accurate predictions with reduced inference time. This feature is particularly critical in a dynamic bio-energy system where the pollutant formation is affected by fluctuating feedstock characteristics, operative conditions and system loads. To ensure that abnormal emissions are detected as early as possible and that corrective action is timely, DL-based systems allow for the continued learning along with fast reaction to resolve it accordingly. For example, deep learning coupled with flame radical imaging enables to predict NOx emissions in case of biomass combustion with high accuracy better than the image processing-based and machine-learned models [33]. Additionally, the ability of deep learning models to learn for long periods and adapt themselves to varying conditions makes them very well suited for environmental monitoring in which systems need to be able to grow with incoming data streams and maintain good predictive performance over time [4]. This flexibility is important for ensuring the efficacy of pollution detection systems in the presence of different operating conditions and feedstocks that are typical to bioenergy processes [34]. On the other hand, applying deep learning features for real-time process monitoring in practical industrial processes would require computation efficiency and algorithm robustness to consider the applicability. [35] For instance, while ensemble methods may cushy slightly longer prediction times, the approach is always appropriate for monitoring and it can be useful to obtain coincidence intervals in order to robustly quantify uncrusty [36].

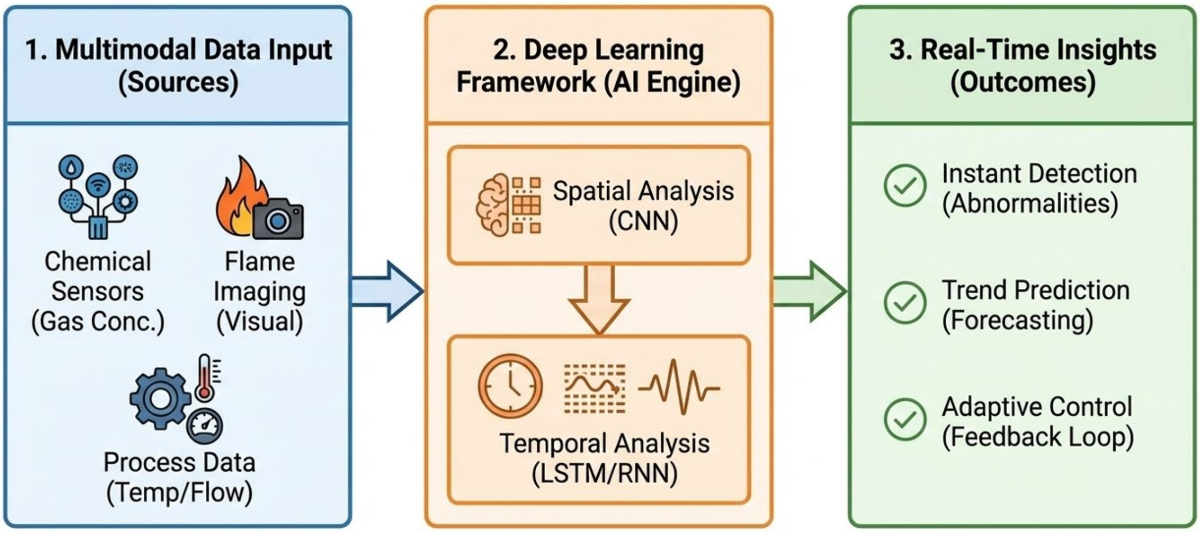

Figure 3. Deep Learning Architecture for Real-Time Bio-Energy Pollutant Detection

The **figure 3** integrates multimodal data sources—including chemical sensors, flame imagery, and spectral data—into deep learning models like CNNs and LSTMs to handle spatial and temporal complexities.

The system enables real-time detection of nonlinear pollutant patterns and facilitates adaptive control to ensure environmental compliance despite fluctuating feedstock conditions.

Moreover, deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks are well suited for handling spatial, temporal, and spatio-temporal data. These models can capture transient emission patterns, sensor drift effects, and short-term process instabilities, making them highly effective for real-time monitoring applications. When deployed at the edge or integrated with industrial control systems, DL models enable low-latency decision-making and adaptive emission control.

3.1. Data sources and sensor integration

DL-based pollutant identification systems use various and dissimilar sources of data acquired in the different sensors deployed within bio-energy plants. Concentration of gases can be continuous monitored using electrochemical, metal oxide and infrared sensors for main pollutants such as CO, NO_x, SO_2, CH_4 and H_2S which have high sensitivity and fast response in order to track the real time emissions.

Flame images and exhaust plume visuals taken by cameras are key sources of optical combustion related data such as, quality of combustion, flame stability and particulates generation. Detection of visual patterns that indicate incomplete burning or potential abnormal emissions is usually done in these images using convolutional neural networks. In addition, dedicated sensors such as lidar and differential absorption spectroscopy can observe greenhouse gases and trace pollutants in plumes at high spatial and temporal resolution complementing information for sophisticated deep learning type models [37]. In addition to pollutant measurements, the operational conditions involving temperature, pressure, flow rates and fuel composition are essential to provide a context for sensor readings and enhance model precision.

Both Fourier-transform infrared (FTIR) spectrometers and laser-based analyzers provide spectral information that allows the identification as well as quantification of multiple gas species in a single measurement. Such high-dimensional data are particularly amenable to deep learning models, which can be trained to identify the minute spectral features that are characteristic of different pollutants even in a noisy context. Combining interpretable machine learning data processing techniques with state of the art deep-learning network architectures, like LSTM and CNN, further improves prediction performance and provides an idea on how much operational input parameters influence the model [38]. Furthermore, by being able to capture the dynamic of sequential time series data, recurrent neural networks especially LSTMs are good at predicting future emission trends and operation changes in a timely manner [38]. Effective noise reduction methods including wavelet transform and Kalman Filter are also important to enhance the quality of data for robustness in DL models against environmental variations and sensor measurement uncertainties. [4].

Operational parameters like temperature, pressure, air flow rates and fuel feed rate are then added so as to get contextual insights on the status of the system. Through data fusion of multi-sensor data, DL contributes to solve the problem by increasing robustness, decreasing false alarms and enhancing reliability leading to accurate and real time pollutant detection in complex bio-energy systems. This shared multimodal data integration approach gives a holistic overview of the system, and DL models can capture subtle relationships and enhance the prediction of pollutant concentrations compared to using single sensors [39]. The combination of spatial and temporal data by using deep learning approaches, such as the use of convolutional neural networks for spatial analysis and recurrent neural networks for handling the time series nature data, improves predictive models' accuracy by efficiently integrating multiple information streams [40].

4. Deep learning architectures used

A range of deep learning architectures has been adopted for pollutant monitoring in bio-energy production and utilization systems. These architectures are designed to handle heterogeneous sensor data, nonlinear emission behavior, and rapidly changing operating conditions, thereby enabling accurate and real-time emission analysis. The **figure 4** categorizes key neural network models (CNN, RNN/LSTM, Auto encoders, Hybrid) used to process heterogeneous spatial and temporal data. It illustrates how these architectures enable accurate anomaly detection, real-time emission monitoring, and predictive control in complex bio-energy processes.

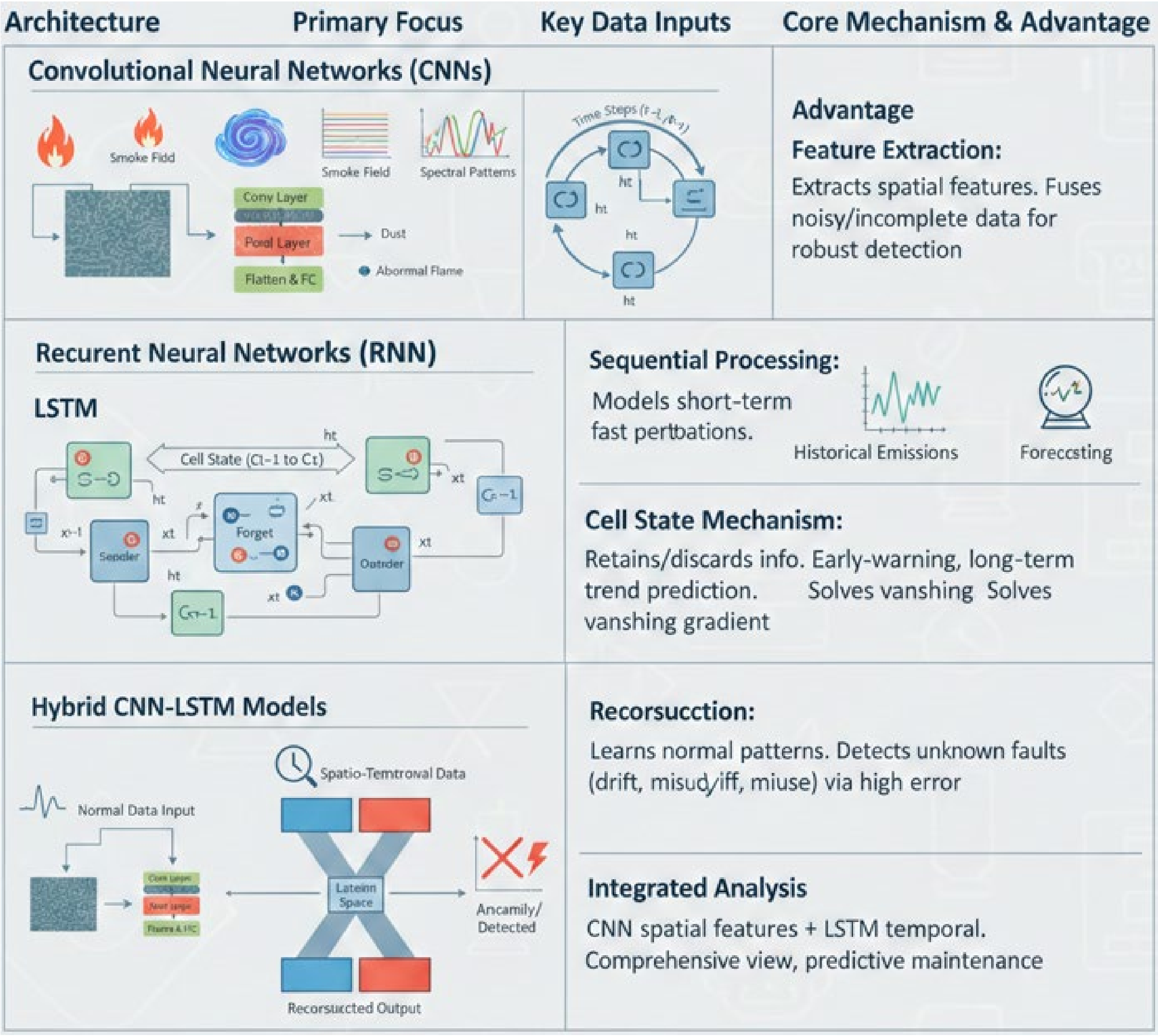

Figure 4. Deep Learning Architectures for Pollutant Monitoring in Bio-Energy Systems

4.1. Convolutional Neural Networks (CNNs)

These are widely employed in bioenergy emission monitoring for spatial and high-dimensional data analysis, such as flame pictures, smoke field distributions, exhaust plume visuals, spectral patterns. Such networks can extract appropriate spatial features reflecting the quality of combustion and emission to accurately characterize incomplete combustion, dust formation and abnormal flame patterns from different operating conditions. For example, CNNs can fuse data from the thermal camera with gas sensor signals to deal with incomplete or noisy information, resulting in a more robust detection system [41-49]. The CNNs can also directly learn complex patterns from raw sensor inputs (e.g., identifying specific pollutant signatures in the spectral data), further alleviating the reliance on hand-crafted feature engineering [50]. Moreover, combined approaches with CNN and recurrent neural networks or long short-term memory networks hybrids can consider both spatial and temporal dimensions of environmental data to gain a better understanding on pollution dynamics as well as predictive models [51-59].

4.2. Recurrent Neural Networks (RNNs)

These are intended for handling time series data and may be used for online environmental pollution concentration monitoring. Through the modelling of short-term temporal dependencies between sensor signals and operating conditions, RNNs allow for monitoring of fast perturbations in emissions due to changes in feedstock characteristics, system load or process upsets. They are thus particularly suited to model the temporal dynamics and dependencies inherent in emission data [60] as they can store an internal history of past inputs. In particular, Long Short-Term Memory networks (LSTM) which is a member of RNN family solves the vanishing gradient problem, and therefore has an ability to model long-term dependencies in time-series data such as pollutant forecasting and capturing emerging trends [61-69].

4.3. Long Short-Term Memory (LSTM) Networks

A more advanced RNN form to overcome the shortcomings of standard RNNs, long short-term memory (LSTM) has been proposed to capture long-range temporal dependencies in emission data. In bio-energy networks, LSTM models are commonly used to predict slow accumulation of pollutants and further emissions lagged responses as well as projected concentration trends, thus enabling early-warning and proactive emission control. Their gating (the input, the forget and the output gates) allows selectively to retain or discard information over long timescales, making it particularly suitable for modelling pollutant concentration with complex non-linear temporal dynamics [70]. This feature would enable LSTMs to discriminate transient spikes and sustained pollution level increases, providing a more comprehensive monitoring of system stability and potential environmental effects [71-79].

4.4. Auto encoders

They are primarily used for unsupervised anomaly detection and sensor fault diagnosis. By training an auto encoder based on a normal operation emission data and similar to process data, anomalies caused by abnormal emissions, sensor drifting or equipment misusing can be found jeopardizing the process, even with only few labelled fault data. In particular, auto encoders reconstruct input data and a large difference between the original and reconstructed data is indicative of an alarm event (e.g., an emission of pollution or sensor failure) [80-85]. Bi-directional LSTM auto encoder has demonstrated excellent performance of anomaly detection in time series data and is superior to normal LSTM-auto encoder such as wind power dataset [86]. This latter capability is very important for site/process monitoring systems where new types of faults may occur, thus making supervised anomaly detection unfeasible because of the lack of pre-labelled anomalous data.

4.5. Hybrid CNN–LSTM Models

These combine CNN-based spatial feature extraction with LSTM-based temporal modelling to capture instantaneous emission characteristics and their change over time. This integrated method is expected to significantly enhance the accuracy and robustness of real-time pollutant detection and prediction in complex bio-energy production and utilization processes. This interplay provides a comprehensive view on pollutant production and emission dynamics by observing both spatial patterns and their temporal change, which is a necessary condition for predictive maintenance practices and reduction of emissions [87-95]. This architectural mixture greatly enhances the accuracy in anomaly detection and prediction by putting together expr variable swishes of both convolutional layers and recurrent architectures [96-99]. What's more, the attention mechanisms similar to the one in Dual-Stage Attention RNNs can be added to improve forecasting through learning on how dynamically to weight relevant features and critical time steps, which leads to more interpretable and accurate pollution prediction [100].

Table 2. Deep Learning Architectures for Pollutant Monitoring in Bio-Energy Systems

Architecture	Key Characteristics	Typical Input Data	Main Applications in Bio-Energy Systems	Advantages
Convolutional Neural Networks (CNNs)	Designed for spatial and high-dimensional feature extraction; automatically learn complex spatial patterns	Flame images, smoke field distributions, exhaust plume visuals, spectral and thermal images, fused sensor data	Detection of incomplete combustion, dust formation, abnormal flame patterns, spatial pollutant characterization	High spatial feature extraction capability; reduces need for hand-crafted features; robust to noisy data
Recurrent Neural Networks (RNNs)	Models short-term temporal dependencies using internal memory	Time-series gas sensor signals, emission concentration data, operating condition logs	Real-time monitoring of fast emission fluctuations due to feedstock variation, load changes, or process disturbances	Effective for sequential data; captures temporal emission dynamics
Long Short-Term Memory (LSTM)	Advanced RNN with gating mechanisms (input, forget, output) to capture long-term dependencies	Long-term pollutant concentration time series, delayed emission responses	Pollutant forecasting, trend analysis, early-warning systems, discrimination between transient spikes and sustained emissions	Handles vanishing gradient problem; accurate long-term prediction and trend detection
Autoencoders (AE)	Unsupervised learning models focused on data reconstruction and deviation detection	Normal-operation emission data, sensor signals, process variables	Anomaly detection, sensor fault diagnosis, abnormal emission identification	Effective with limited labelled fault data; suitable for unknown or emerging faults
Hybrid CNN–LSTM Models	Combines CNN-based spatial feature extraction with LSTM-based temporal modelling	Multimodal spatial–temporal data (images + sensor time series)	Real-time pollutant prediction, anomaly detection, predictive maintenance, emission trend forecasting	High robustness and accuracy; captures both spatial patterns and temporal evolution
Attention-Enhanced Hybrid Models	Incorporates attention mechanisms to dynamically weight important features and time steps	Multivariate emission and operational datasets	Improved interpretability and precision in pollution forecasting and control	Enhanced prediction accuracy and explainability

The **table 2** summarizes the main deep learning architectures used for pollutant monitoring in bio-energy systems, highlighting their input types, key characteristics, and applications. It also outlines their advantages in enabling accurate, real-time emission detection, anomaly identification, and predictive control for sustainable bio-energy operations.

The overall adoption of these deep learning architectures allows for better early detection of irregular emission patterns, more predictive emission control and an efficient operation of sustainable and environmentally friendly bio-energy systems.

5. Real-time implementation framework

A deep learning–based real-time pollutant detection framework for bio-energy plants is designed to ensure continuous monitoring, rapid decision-making, and adaptive control under dynamic operating conditions. The framework typically begins with **sensor data acquisition and pre-processing**, where data are collected from gas sensors, optical cameras, spectroscopic instruments, and process sensors distributed across the plant. Pre-processing steps such as noise filtering, normalization, synchronization of multi-sensor streams, and handling of missing data are essential to improve data quality and ensure reliable model inputs in real time. Subsequently, these refined data streams are fed into a distributed deep learning architecture, often leveraging hybrid CNN-

LSTM models or similar advanced neural networks, which are optimized for rapid inference to identify subtle pollutant signatures and predict their concentrations instantaneously [101-109].

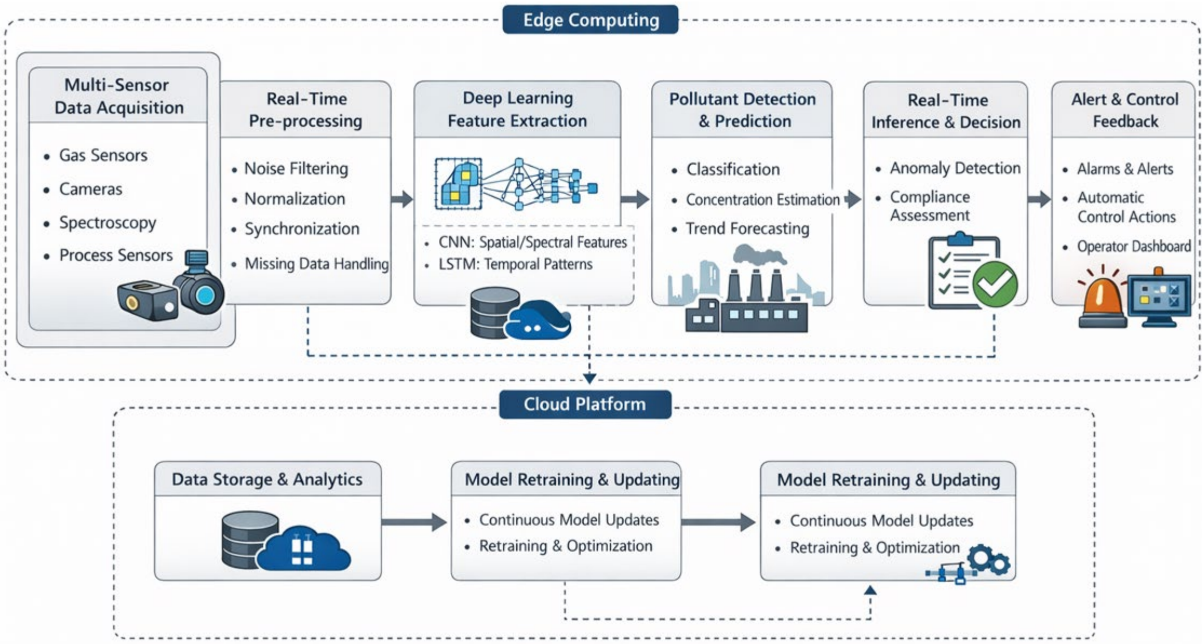

Figure 5. Real-Time Deep Learning–Based Pollutant Detection Framework for Bio-Energy Plants

The **figure 5** illustrates an end-to-end real-time framework integrating multi-sensor data acquisition, deep learning–based feature extraction, and low-latency inference for continuous pollutant monitoring in bio-energy plants. Edge–cloud architecture enables rapid alert generation and automated control actions, while supporting continuous model updating for adaptive and sustainable emission management.

The next stage involves **feature extraction using deep learning models**, where raw or minimally processed data are transformed into meaningful representations. Convolutional neural networks extract spatial features from images and spectral data, while recurrent or LSTM networks capture temporal patterns from time-series sensor measurements. This automated feature learning reduces dependence on manual feature engineering and improves robustness under varying feedstock and operating conditions. The extracted features are then fed into detection and prediction modules, which utilize trained deep learning models to classify pollutant types, quantify their concentrations, and forecast future emission trends. This enables real-time monitoring and proactive mitigation strategies, as the deep learning system can optimize fuel-air ratios to reduce emissions and consumption, or adjust parameters in chemical reactors to balance productivity and energy efficiency [110-115].

In the **real-time inference and pollutant classification** stage, trained deep learning models are deployed to continuously estimate pollutant concentrations, classify emission types, and detect abnormal emission patterns. These predictions are generated with low latency, enabling near-instantaneous assessment of environmental performance and regulatory compliance. Such systems can then trigger alarms, generate alerts, and provide actionable insights to plant operators, facilitating immediate intervention to rectify operational anomalies or optimize process parameters for emission reduction [116]. This real-time feedback loop ensures that bio-energy systems operate within permissible emission limits while maximizing efficiency and minimizing environmental impact.

Based on inference results, **alert generation and control system feedback** mechanisms are activated. When pollutant levels exceed predefined thresholds or abnormal trends are detected, alerts are issued to plant operators and corrective actions such as airflow adjustment, fuel feed control, or emission treatment activation can be automatically initiated through integration with plant control systems. This automated response capability significantly reduces human intervention, ensuring swift and precise mitigation of environmental risks and optimizing plant performance for sustainable bio-energy production [117-122].

Finally, the framework supports **continuous model updating using new operational data**. As new data are generated during plant operation, models can be periodically retrained or fine-tuned to account for sensor aging, equipment wear, and changing process conditions. To achieve both low latency and scalability, **edge computing** is commonly used for real-time inference near the sensors, while **cloud-based platforms** support large-scale data storage, model training, and long-term analytics. This hybrid edge–cloud approach ensures efficient, scalable, and reliable real-time pollutant monitoring in bio-energy systems.

6. Benefits of deep learning-based monitoring

Deep learning methods for monitoring in bio-energy generation and utilization system have many advantages compared with traditional pollutant detection method. One of the major advantages is that they have high detection performance even in cases of variable operation conditions–because deep learning models can work with complex non-linear connection among sensor signals and operating parameters, to emission behavior. This provides sure identification of pollutants, even if the properties of the feedstocks, humidity or the loads are varying. Other notable benefits are the immediate response in real time, and the early warning, so an emission abnormality is detected as soon as it arises and proactive measures can be taken before pollutants exceed legal limits. Deep learning–enabled monitoring also results in less reliance on manual sampling and laboratory testing, which are often time-consuming, expensive, as well as not applicable for continuous monitoring. The use of the sensor-based automation reduces the need for costly human surveillance made it possible to perform continuous monitoring of emissions. Furthermore, they facilitate the adaptation to new feedstocks and process changes as models can be retrained or fine-tuned with freshly obtained operational data making them still robust and relevant in the long-term. In addition, deep learning improves overall compliance to environmental regulations by delivering accurate, real-time and verifiable emission data which can help manufacturers report in a timely manner while ensuring compliance with the latest regulatory requirements. These benefits together lead to the cleaner bio-energy production, lower environmental impact and better operation reliability and sustainability for bio-energy system.

7. Challenges and research gaps

Despite the progress in using deep learning for pollutant monitoring in the bio-energy systems, challenges and research gaps are still present which impede its large-scale adoption by industry. One such difficult problem is that of limited emissions label datasets, as establishing trust and ground truth values for emission data is costly in terms of both the time involved and expense, and often requires laboratory quality instruments. This constrained availability prevents the training of supervised models and generalizing over different plants and operating conditions. The other reason lies on the sensor drift and data noise especially in harsh bio-energy environments with hot temperature, humidity, dust and corrosive gas. These effects will degrade the long-term performance of sensor leading to inaccurate measurement and unstable model. The interpretability and transparency of model are greatly concerned, since the deep learning models are "black box" method. Regulation and operator´s trust It is crucial for the regulation as well as for the confidence of operators, to know how are models make following predictions or forecast alarms. Furthermore, intensive computations during testing on real-time deployment is another difficult task, for large-scale architecture which are not affordable to tiny edge devices due to their huge memory and computing need. Yet another practical barrier is the inability of advanced data-driven monitoring systems to coexist with traditional industrial control systems since deep learning work on one system need not necessarily be compatible with legacy infrastructure. To address these challenges, future explorative works in the direction of physics-informed DL will require solution approaches that incorporate domain knowledge to enhance interpretability, data-efficient transfer learning methods and lightweight/low-energy models for edge deployments. Searching the above gaps and shortcomings will be a future research direction, towards its reliable and scalable deep learning-based pollutant monitoring for industrial-grade bio-energy production and utilization systems.

8. Future perspectives

Deep learning in combination with ubiquitous digital technologies is expected to have a significant influence on the future of pollutant predictive monitoring and control for bio-energy systems. The coalescing of deep learning and the Internet of Things (IoT) can facilitate denser sensor networks, perpetual data streaming in addition to ubiquitous IoT-based thermal management interconnection among bio-energy plants resulting with more extensive real-time emissions monitoring. At the other hand digital twins (virtual representations of a real-world object) will let calculate (by deep learning-based model for example) emission behaviors under different operation modes, to optimize control strategies and predict effects from process changes ahead of realization. Combining with RL: Reinforcement learning can also be employed alongside deep-learning-based monitoring systems for realizing autonomous emissions regulation, where the control strategies are refined on line by interacting with the environment to minimize emission at a permissible level of efficiency. In addition, the incorporation of XAI will be crucial to improve transparency and interpretability of models. XAI may increase the operator's confidence and regulatory acceptance of AI based emission monitoring system by describing the features of importance, decision path and confidence level. However, federated learning also may be an attractive alternative to continuously updating a model with new bio-energy plants. Federated learning enables the separation of model training and raw data sharing, thereby safeguarding sensitive patients' data, whilst improving models' robustness and generalization under even extreme operative settings. That are expected to convert what reactive pollutant sensors are now using deep learning into a new class of proactive, intelligent emission management systems that will help promote cleaner, energy efficient and sustainable production and use of bio-energy.

9. Conclusion

This study demonstrates that deep learning–based frameworks offer a reliable and effective solution for real-time pollutant detection in bio-energy production and utilization systems. By integrating multi-sensor data with advanced deep learning architectures, the proposed approach captures the complex and dynamic emission behaviors associated with varying feedstocks and operating conditions. Compared with conventional monitoring techniques, deep learning models provide higher prediction accuracy, faster response, and improved adaptability, enabling early identification of abnormal emission patterns and timely corrective actions. Despite existing challenges related to data availability, sensor reliability, computational requirements, and model transparency, ongoing progress in sensor technology, edge computing, and explainable artificial intelligence is steadily improving practical deployment. Overall, the findings highlight that intelligent, data-driven emission monitoring can strengthen environmental compliance, enhance operational efficiency, and reduce the environmental footprint of bio-energy systems, supporting their role as a sustainable component of future energy infrastructures.

Author Contributions

Hemlata Suresh Gaikwad: Conceptualization, methodology, data curation, formal analysis, writing – original draft. **Nidhi Sharma**: Methodology, investigation, validation, writing – review and editing. **Shital Y. Solanke**: Data curation, software, visualization, formal analysis. **Swati Mukesh Dixit**: Investigation, resources, writing – review and editing. **Anant Sidhappa Kurhade**: Supervision, conceptual guidance, critical review, technical validation, writing – review and editing.

Acknowledgments

The authors would like to express their sincere gratitude to Dr. D. Y. Patil Institute of Technology and DPGU, School of Technology and Research - Dr. D. Y. Patil Unitech Society, Pimpri, Pune for providing the necessary support and research infrastructure.

Conflict of interest

The authors declare no conflict of interest

References

1. Magazzino C. The impact of deep learning on environmental science. Deleted Journal. 2024 Jun 24;1(1). https://doi.org/10.1186/s44329-024-00003-5
2. García A, Sáez Y, Harris I, Huang X, Collado E. Advancements in air quality monitoring: a systematic review of IoT-based air quality monitoring and AI technologies. Artificial Intelligence Review. 2025 Jun 11;58(9). https://doi.org/10.1007/s10462-025-11277-9
3. Afoma UM, Singh S, Mishra AK, Sharma CK, Gupta K, Mishra MK, Roy B, Verma VV, Sharma VK. Integrating Artificial Intelligence in Environmental Monitoring: A Paradigm Shift in Data-Driven Sustainability. EcoHealth. 2025 Aug 28. https://doi.org/10.1007/s10393-025-01752-8
4. Ojadi JO, Owulade OA, Odionu CS, Onukwulu EC. Deep Learning Models for Predicting and Mitigating Environmental Impact of Industrial Processes in Real-Time. International Journal of Scientific Research in Science Engineering and Technology. 2025 Mar 16;12(2):119. https://doi.org/10.32628/ijsrset25122109
5. Prakash N, Zielinski O. AI-enhanced real-time monitoring of marine pollution: Part 1—A state-of-the-art and scoping review. Frontiers in Marine Science. 2025 Apr 28;12. https://doi.org/10.3389/fmars.2025.1486615
6. Balakumar S, Narayanan M, Kamaraj M, Aravind J. Harnessing artificial intelligence for sustainable environmental remediation: A review. International Journal of Environmental Science and Technology. 2025 Jun 2;22(13):13189. https://doi.org/10.1007/s13762-025-06528-9
7. Alghieth M. Sustain AI: A multi-modal deep learning framework for carbon footprint reduction in industrial manufacturing. Sustainability. 2025 May 2;17(9):4134. https://doi.org/10.3390/su17094134
8. Patil M. Environmental sustainability in the age of deep learning: Balancing technological advancement with ecological responsibility. Deleted Journal. 2024 May 2;20:2377. https://doi.org/10.52783/jes.3221
9. Sekar P, Mohan J. Synthetic generation and detection of crown-of-thorns starfish instance retrieval in underwater images. Research Square. 2024 Apr 9. https://doi.org/10.21203/rs.3.rs-4198952/v1
10. Fan Z, Yan Z, Wen S. Deep learning and artificial intelligence in sustainability: A review of SDGs, renewable energy, and environmental health. Sustainability. 2023 Sep 8;15(18):13493. https://doi.org/10.3390/su151813493
11. Coscia P, Plataniotis KN, Panigrahi BK, Zhai Y. Editorial: Deep learning for industrial applications. Frontiers in Computer Science. 2025 Aug 12;7. https://doi.org/10.3389/fcomp.2025.1664990
12. Anbarasu K, Sundaram T, Sathishkumar K, Alam MM, Al-Sehemi AG, Devarajan Y. Harnessing artificial intelligence for sustainable bioenergy: Revolutionizing optimization, waste reduction, and environmental sustainability. Bioresource Technology. 2024 Nov 1;131893. https://doi.org/10.1016/j.biortech.2024.131893
13. Rane NL, Kaya Ö, Rane J. Advancing the Sustainable Development Goals (SDGs) through artificial intelligence, machine learning, and deep learning. 2024. https://doi.org/10.70593/978-81-981271-8-1_4
14. Gao S, Guan X, Cao X, Zhi-li B, Wang C, Zhan Y, Yu H. Optimization of decision support technology for offshore oil condition monitoring with carbon neutrality as the goal in the enterprise development process. PLoS ONE. 2025 Mar 25;20(3). https://doi.org/10.1371/journal.pone.0319858
15. Wang Z, Peng X, Xia A, Shah AA, Huang Y, Zhu X, Liao Q. The role of machine learning to boost bioenergy and biofuels conversion. Bioresource Technology. 2021 Oct 8;343:126099. https://doi.org/10.1016/j.biortech.2021.126099
16. Marzban N, Psarianos M, Herrmann C, Schulz-Nielsen L, Olszewska-Widdrat A, Arefi A, et al. Smart integrated biorefineries in bioeconomy: A concept toward zero-waste, emission reduction, and self-sufficient energy production. Biofuel Research Journal. 2025 Mar 1;12(1):2319. https://doi.org/10.18331/brj2025.12.1.4
17. Kumar V, Shahin K. Artificial intelligence and machine learning for sustainable manufacturing: Current trends and future prospects. Intelligent and Sustainable Manufacturing. 2025 Jan 1;2(1):10002. https://doi.org/10.70322/ism.2025.10002
18. Matei A, Butean A, Zamfirescu CB, Marcos JD. Designing a conceptual digital twin architecture for high-temperature heat upgrade systems. Applied Sciences. 2025 Feb 22;15(5):2350. https://doi.org/10.3390/app15052350
19. Shahverdi N, Saffari A, Amiri B. A systematic review of artificial intelligence and machine learning in energy sustainability: Research topics and trends. Energy Reports. 2025 May 13;13:5551. https://doi.org/10.1016/j.egyr.2025.05.021

20. Nair LG, Verma P. Harnessing carbon potential of lignocellulosic biomass: Advances in pretreatments, applications, and the transformative role of machine learning in biorefineries. Bioresources and Bioprocessing. 2025 Sep 13;12(1). https://doi.org/10.1186/s40643-025-00935-z
21. Cao L, Su J, Saddler J, Cao Y, Wang Y, Lee G, Siang LC, Pinchuk R, Li J, Gopaluni RB. Real-time tracking of renewable carbon content with AI-aided approaches during co-processing of biofeedstocks. Applied Energy. 2024 Feb 10;360:122815. https://doi.org/10.1016/j.apenergy.2024.122815
22. Nguyen TH, Paramasivam P, Dong VH, Le HC, Nguyen DC. Harnessing a Better Future: Exploring AI and ML Applications in Renewable Energy. JOIV International Journal on Informatics Visualization. 2024 Mar 16;8(1):55. https://doi.org/10.62527/joiv.8.1.2637
23. Osman AI, Fang B, Zhang Y, Liu Y, Yu J, Farghali M, Rashwan AK, Chen Z, Chen L, Ihara I, Rooney DW, Yap P. Life cycle assessment and techno-economic analysis of sustainable bioenergy production: A review. Environmental Chemistry Letters. 2024 Feb 2;22(3):1115. https://doi.org/10.1007/s10311-023-01694-z
24. Christianides D, Bagaki DA, Timmers RA, Zrimec MB, Theodoropoulou A, Angelidaki I, Kougias P, Zampieri G, Kamergi N, Napoli A, Malamis D, Mai S, Barampouti EM. Biogenic CO_2 emissions in the EU biofuel and bioenergy sector: Mapping sources, regional trends, and pathways for capture and utilisation. Energies. 2025 Mar 10;18(6):1345. https://doi.org/10.3390/en18061345
25. El-Araby R. Biofuel production: Exploring renewable energy solutions for a greener future. Biotechnology for Biofuels and Bioproducts. 2024 Oct 15;17(1). https://doi.org/10.1186/s13068-024-02571-9
26. Unuofin JO, Iwarere SA, Daramola MO. Embracing the future of circular bio-enabled economy: Unveiling the prospects of microbial fuel cells in achieving true sustainable energy. Environmental Science and Pollution Research. 2023 Jul 22;30(39):90547. https://doi.org/10.1007/s11356-023-28717-0
27. Alao KT, Gilani SIU, Sopian K, Alao TO, Oyebamiji DS, Oladosu TL. Biomass and organic waste conversion for sustainable bioenergy: A comprehensive bibliometric analysis of current research trends and future directions. International Journal of Renewable Energy Development. 2024 May 15;13(4):750. https://doi.org/10.61435/ijred.2024.60149
28. Paolini V, Petracchini F, Segreto M, Tomassetti L, Naja N, Cecinato A. Environmental impact of biogas: A short review of current knowledge. Journal of Environmental Science and Health Part A. 2018 Apr 13;53(10):899. https://doi.org/10.1080/10934529.2018.1459076
29. Feng L, Aryal N, Li Y, Horn SJ, Ward AJ. Developing a biogas centralised circular bioeconomy using agricultural residues: Challenges and opportunities. Science of the Total Environment. 2023 Jan 17;868:161656. https://doi.org/10.1016/j.scitotenv.2023.161656
30. Ahmad I, Sana A, Kano M, Cheema II, Menezes BC, Shahzad J, Ullah Z, Khan M, Habib A. Machine learning applications in biofuels' life cycle: Soil, feedstock, production, consumption, and emissions. Energies. 2021 Aug 18;14(16):5072. https://doi.org/10.3390/en14165072
31. Jacob-Lopes E, Zepka LQ. Frontiers in Bioenergy and Biofuels. InTech; 2017. https://doi.org/10.5772/63185
32. Leng L, Li T, Zhan H, Rizwan MS, Zhang W, Peng H, Yang Z, Li H. Machine learning-aided prediction of nitrogen heterocycles in bio-oil from the pyrolysis of biomass. Energy. 2023 May 29;278:127967. https://doi.org/10.1016/j.energy.2023.127967
33. Li N, Lu G, Li X, Yan Y. Prediction of NOx emissions from a biomass-fired combustion process based on flame radical imaging and deep learning techniques. Combustion Science and Technology. 2015 Oct 5;188(2):233. https://doi.org/10.1080/00102202.2015.1102905
34. Mohammadi M, Saloğlu D, Dertli H, Ghaffari-Moghaddam M. Data-driven modeling for the prediction of stack gas concentration in a coal-fired power plant in Türkiye. Water Air & Soil Pollution. 2024 Apr 29;235(5). https://doi.org/10.1007/s11270-024-07107-3
35. Chen X, Lei Y. Intelligent optimization of combustion process and NOx emission control of power plant boiler based on deep learning and multi-objective optimization. EAI Endorsed Transactions on Energy Web. 2025 Sep 12;12. https://doi.org/10.4108/ew.7188
36. Han Z, Li J, Hossain MdM, Qi Q, Zhang B, Xu C. An ensemble deep learning model for exhaust emissions prediction of heavy oil-fired boiler combustion. Fuel. 2021 Sep 15;308:121975. https://doi.org/10.1016/j.fuel.2021.121975
37. Hasan MR, Khatoon R, Akter J, Mohammad N, Kamruzzaman Md, Shahana A, Saha S. AI-driven greenhouse gas monitoring: Enhancing accuracy, efficiency, and real-time emissions tracking. AIMS Environmental Science. 2025 Jan 1;12(3):495. https://doi.org/10.3934/environsci.2025023
38. Poudel L, Tincher D, Phan DN, Bhowmik R. Deep learning-enhanced amine emission monitoring and performance analysis in industrial carbon capture plants. arXiv. 2025 Sep 5. http://arxiv.org/abs/2509.05241
39. Saimon AI, Yangue E, Yue X, Kong Z, Liu C. Advancing additive manufacturing through deep learning: A comprehensive review of current progress and future challenges. arXiv. 2024 Mar 1. http://arxiv.org/abs/2403.00669
40. Villegas-Ch W, Gaibor-Naranjo W, Sánchez-Viteri S. Application of deep learning techniques for the optimization of industrial processes through the fusion of sensory data. International Journal of Computational Intelligence Systems. 2024 Jul 18;17(1). https://doi.org/10.1007/s44196-024-00596-4

41. Li JX, Zhang T, Zhu Y, Chen Z. Artificial general intelligence (AGI) for the oil and gas industry: A review. arXiv. 2024 Jun 1. https://arxiv.org/abs/2406.00594
42. Babakhouya A, Naji A, Daaif A, Hnini A. Leveraging artificial intelligence in the agri-food industry: A comprehensive review. E3S Web of Conferences. 2023;469:79. https://doi.org/10.1051/e3sconf/202346900079
43. Abboud M. Leveraging machine learning for multi-source data enrichment and analytics in air quality monitoring and crowd sensing. HAL. 2023 Nov 8. https://theses.hal.science/tel-04323377
44. Ao SI, Gelman L, Karimi HR, Tiboni M. Advances in machine learning for sensing and condition monitoring. Applied Sciences. 2022 Dec 3;12(23):12392. https://doi.org/10.3390/app122312392
45. Gupta R, Ouderji ZH, Uzma U, Yu Z, Sloan WT, You S. Machine learning for sustainable organic waste treatment: A critical review. npj Materials Sustainability. 2024 Apr 8;2(1). https://doi.org/10.1038/s44296-024-00009-9
46. Pariaman H, Luciana GM, Wisyaldin MK, Hisjam M. Anomaly detection using LSTM-autoencoder to predict coal pulverizer condition in coal-fired power plants. Evergreen. 2021 Mar 1;8(1):89. https://doi.org/10.5109/4372264
47. Shin Y, Na K, Kim SE, Kyung EJ, Choi HG, Jeong J. LSTM-autoencoder-based detection of time-series noise signals for water supply and sewer pipe leakages. Water. 2024 Sep 16;16(18):2631. https://doi.org/10.3390/w16182631
48. Abshari D, Sridhar M. A survey of anomaly detection in cyber-physical systems. arXiv. 2025 Feb 18. http://arxiv.org/abs/2502.13256
49. Iqbal A, Amin R, Alsubaei FS, Alzahrani A. Anomaly detection in multivariate time series data using deep ensemble models. PLoS ONE. 2024 Jun 6;19(6). https://doi.org/10.1371/journal.pone.0303890
50. Bereketoğlu AB. Hybrid meta-learning framework for anomaly forecasting in nonlinear dynamical systems via physics-inspired simulation and deep ensembles. arXiv. 2025 Jun 15. http://arxiv.org/abs/2506.13828
51. Wan A, Yang J, Chen T, Li K, Zhou Q. Dynamic pollution emission prediction method of a combined heat and power system based on hybrid CNN–LSTM model and attention mechanism. Environmental Science and Pollution Research. 2022 May 17;29(46):69918. https://doi.org/10.1007/s11356-022-20718-9
52. Shrivastava S. Air pollution forecasting using deep learning models with hybrid approaches: A review. International Journal for Research in Applied Science and Engineering Technology. 2024 Jun 28;12(6):1798. https://doi.org/10.22214/ijraset.2024.63401
53. Tüzün U. Artificial intelligence-assisted dynamic control of environmental emissions from hybrid energy process plants. Frontiers in Energy Research. 2020 Jul 31;8. https://doi.org/10.3389/fenrg.2020.00179
54. Berkani MRA, Chouchane A, Himeur Y, Ouamane A, Amira A. An intelligent edge-deployable indoor air quality monitoring and activity recognition approach. arXiv. 2023 Nov 8. http://arxiv.org/abs/2311.03920
55. Kurhade AS, Gadekar T, Siraskar GD, Jawalkar SS, Biradar R, Kadam AA, Yadav RS, Dalvi SA, Waware SY, Mali CN. Thermal performance analysis of electronic components on different substrate materials. J Mines Met Fuels. 2024 Oct 1;72(10). https://doi.org/10.18311/jmmf/2024/45569
56. Kurhade AS, Siraskar GD, Jawalkar SS, Gadekar T, Bhambare PS, Biradar R, Yadav RS, Waware SY, Mali CN. The impact of circular holes in twisted tape inserts on forced convection heat transfer. J Mines Met Fuels. 2024 Oct 16;72(9):1005-12. https://doi.org/10.18311/jmmf/2024/45505
57. Kurhade AS, Bhambare PS, Desai VP, Murali G, Yadav RS, Patil P, Gadekar T, Biradar R, Kirpekar S, Charwad GA, Waware SY. Investigating the effect of heat transfer influenced by wavy corrugated twisted tape inserts in double pipe heat exchangers. J Adv Res Fluid Mech Therm Sci. 2024;122:146-55. https://doi.org/10.37934/arfmts.122.2.146155
58. Kurhade AS, Murali G, Jadhav PA, Bhambare PS, Waware SY, Gadekar T, Yadav RS, Biradar R, Patil P. Performance analysis of corrugated twisted tape inserts for heat transfer augmentation. J Adv Res Fluid Mech Therm Sci. 2024;121(2):192-200. https://doi.org/10.37934/arfmts.121.2.192200
59. Yadav RS, Nimbalkar A, Gadekar T, Patil P, Patil VN, Gholap AB, Kurhade AS, Dhumal JR, Waware SY. Comparison of experimental and numerical investigation of mono-composite and metal leaf spring. J Mines Met Fuels. 2024 Aug 1;72(8). https://doi.org/10.18311/jmmf/2024/45325
60. Kurhade AS, Warke P, Maniyar K, Bhambare PS, Waware SY, Deshpande S, Harsur S, Ingle M, Kolhe P, Patil PA, Jadhav P. Wind rose analysis of temperature variation with sensor implantation technique for wind turbine. J Adv Res Fluid Mech Therm Sci. 2024;122(1):1-8. https://doi.org/10.37934/arfmts.122.1.118
61. Kurhade AS, Siraskar GD, Bhambare PS, Kaithari DK, Dixit SM, Waware SY. Enhancing smartphone circuit cooling: a computational study of PCM integration. J Adv Res Numer Heat Trans. 2024 Nov 30;27(1):132-45. https://doi.org/10.37934/arnht.27.1.132145
62. Kurhade AS, Darade MM, Siraskar GD, Biradar R, Mahajan RG, Kardile CS, Waware SY, Yadav RS. State-of-the-art cooling solutions for electronic devices operating in harsh conditions. J Mines Met Fuels. 2024 Aug 1;72(8). https://doi.org/10.18311/jmmf/2024/45374
63. Yadav RS, Gadekar T, Gundage V, Patil P, Patil A, Patil P, Patil A, Sutar R, Kurhade AS. Numerical and experimental investigation of the effect of overlapping angle on strength and deformation of curved plate joined using arc welding process. J Mines Met Fuels. 2024 Oct 1;72(10). https://doi.org/10.18311/jmmf/2024/45697

64. Kurhade AS, Bhambare PS, Siraskar GD, Dixit SM, Purandare PS, Waware SY. Computational study on thermal management of IC chips with phase change materials. J Adv Res Numer Heat Trans. 2024;26(1):34-43. https://doi.org/10.37934/arnht.26.1.3443
65. Yadav RS, Gandhi P, Veeranjaneyulu K, Gaji R, Kirpekar S, Pawar D, Khairnar YS, Patil S, Kurhade AS, Patil SP. Influence of plate thickness on the mechanical behaviour of mild steel curved plates: an experimental study. J Mines Met Fuels. 2024 Dec 1;72(12). https://doi.org/10.18311/jmmf/2024/46253
66. Chippalkatti S, Chekuri RB, Ohol SS, Shinde NM, Barmavatu P, Shelkande VD, Murali G, Kurhade AS. Enhancing heat transfer in micro-channel heat sinks through geometrical optimization. J Mines Met Fuels. 2025 Mar 1;73(3). https://doi.org/10.18311/jmmf/2025/47773
67. Raut PN, Dolas AS, Chougule SM, Darade MM, Murali G, Waware SY, Kurhade AS. Green adsorbents for heavy metal removal: a study on zinc ion uptake by Tinospora cordifolia biocarbon. J Mines Met Fuels. 2025 Jan 1;73(1). https://doi.org/10.18311/jmmf/2025/47121
68. Kurhade AS, Siraskar GD, Bhambare PS, Murali G, Deshpande SV, Warke PS, Waware SY. Simulation and analysis of heat transfer in counter-flow helical double-pipe heat exchangers using CFD. Int J Mod Phys C. 2025 Mar 15. https://doi.org/10.1142/S0129183125500433
69. Patil Y, Tatiya M, Dharmadhikari DD, Shahakar M, Patil SK, Mahajan RG, Kurhade AS. The role of AI in reducing environmental impact in the mining sector. J Mines Met Fuels. 2025 May 1;73(5).
70. Waware SY, Ahire PP, Napate K, Biradar R, Patil SP, Kore SS, Kurhade AS. Advancements in heat transfer enhancement using perforated twisted tapes: a comprehensive review. J Mines Met Fuels. 2025 May 1;73(5). https://doi.org/10.18311/jmmf/2025/48438
71. Chougule SM, Murali G, Kurhade AS. Finite element analysis and design optimization of a paddle mixer shaft. J Mines Met Fuels. 2025 May 1;73(5). https://doi.org/10.18311/jmmf/2025/48664
72. Chougule SM, Murali G, Kurhade AS. Failure investigation of the driving shaft in an industrial paddle mixer. J Mines Met Fuels. 2025 May 1;73(5). https://doi.org/10.18311/jmmf/2025/48627
73. Kurhade AS, Sugumaran S, Kolhalkar NR, Karad MM, Mahajan RG, Shinde NM, Dalvi SA, Waware SY. Thermal management of mobile devices via PCM. J Mines Met Fuels. 2025 May 1;73(5):1313-20. https://doi.org/10.18311/jmmf/2025/48437
74. Kurhade AS, Bhavani P, Patil SA, Kolhalkar NR, Chalapathi KS, Patil PA, Waware SY. Mitigating environmental impact: a study on the performance and emissions of a diesel engine fueled with biodiesel blend. J Mines Met Fuels. 2025 Apr 1;73(4):981-9. https://doi.org/10.18311/jmmf/2025/47669
75. Kurhade AS, Siraskar GD, Chekuri RB, Murali G, Pawar P, Patil AR, Waware SY, Yadav RS. Biodiesel blends: a sustainable solution for diesel engine performance improvement. J Mines Met Fuels. 2025 Mar 1;73(3). https://doi.org/10.18311/jmmf/2025/47628
76. Kurhade AS, Siraskar GD, Darade MM, Murali G, Katkar TR, Patil SP, Charwad GA, Waware SY, Yadav RS. Enhancement in heat transfer with nanofluids in double-pipe heat exchangers. J Mines Met Fuels. 2025 Jan 7;73(1):165-72. https://doi.org/10.18311/jmmf/2025/47225
77. Napte K, Kondhalkar GE, Patil SV, Kharat PV, Banarase SM, Kurhade AS, Waware SY. Recent advances in sustainable concrete and steel alternatives for marine infrastructure. Sustain Mar Struct. 2025 Jun 4:107-31. https://doi.org/10.36956/sms.v7i2.2072
78. Kurhade AS, Chougule SM, Kharat PV, Kondhalkar GE, Murali G, Raut PN, Charwad GA, Waware SY, Yadav RS. Integrated approach to enhance vehicle safety: a novel bumper design with energy-absorbing mechanisms. J Mines Met Fuels. 2025 Jan 1;73(1). https://doi.org/10.18311/jmmf/2025/47168
79. Yadav R, Nimbalkar A, Kirpekar S, Patil PJ, Dalvi SA, Jadhav PA, Kurhade AS, Wakchaure GN. Effect of transformed-induced plasticity steel plate thickness on ultimate tensile strength of butt welded joint using Nd:YAG laser. Int J Veh Struct Syst. 2024;16(6):857-62. https://doi.org/10.4273/ijvss.16.6.08
80. Deshpande SV, Pawar RS, Keche AJ, Kurhade A. Real-time surface finish measurement of stepped holding shaft by automatic system. J Adv Manuf Syst. 2025 Feb 25:1-26.
81. Ramani P, Reji V, Sathish Kumar V, Murali G, Kurhade AS. Deep learning-based detection and classification of moss and crack damage in rock structures for geo-mechanical preservation. J Mines Met Fuels. 2025 Mar 1;73(3). https://doi.org/10.18311/jmmf/2025/47760
82. Kurhade AS, Siraskar GD, Deshmukh MT, Patil PA, Chaudhari SS, Kadam AA, Dolas AS, Mahajan RG, Waware SY, Yadav RS. Impact of PCM on heat dissipation from IC chips. J Mines Met Fuels. 2025 Mar 1;73(3). https://doi.org/10.18311/jmmf/2025/47522
83. Kurhade AS, Kharat PV, Chougule SM, Darade MM, Karad MM, Murali G, Charwad GA, Waware SY, Yadav RS. Harnessing the power of plastic waste: a sustainable approach to fuel production. J Mines Met Fuels. 2025 Feb 1;73(2). https://doi.org/10.18311/jmmf/2025/47354
84. Sarode GC, Gholap P, Pathak KR, Vali PSNM, Saharkar U, Murali G, Kurhade AS. Edge AI and explainable models for real-time decision-making in ocean renewable energy systems. Sustain Mar Struct. 2025 Jun 24;7(3):17-42. https://doi.org/10.36956/sms.v7i3.2239
85. Chougule SM, Murali G, Kurhade AS. Dynamic simulation and performance evaluation of vibratory bowl feeders integrated with paddle shaft mechanisms. Adv Sci Technol Res J. 2025;19(7). https://doi.org/10.12913/22998624/203873

86. Chougule SM, Murali G, Kurhade AS. Design and analysis of industrial material handling systems using FEA and dynamic simulation techniques. J Sci Ind Res. 2025 Jun 18;84(6):645-53. https://doi.org/10.56042/jsir.v84i6.17512
87. Kurhade AS, Siraskar GD, Raut PN, Dolas AS, Murali G, Dalvi SA, Waware SY, Yadav RS. Investigating the impact of oxygenated additives on exhaust emissions from unleaded gasoline vehicles. J Mines Met Fuels. 2025 Feb 1;73(2). https://doi.org/10.18311/jmmf/2025/47410
88. Siraskar GD, Kurhade AS, Murali G, Prakash MA, Bharathiraja N, Dharmadhikari DD, Waware SY. Turbulence model comparison and optimal geometry identification in trapped vortex combustors: a RANS-based study. Int J Mod Phys C. 2025 Sep 24:2650020. https://doi.org/10.1142/S0129183126500208
89. Keloth Kaithari D, Kaulage A, Ayyappadas MT, Gholap P, Puri A, Bhandari MA, et al. A review of smart AI systems for real-time monitoring and optimization of ocean-based carbon capture, utilization, and storage networks. Appl Chem Eng. 2025 Sep 17;8(3):ACE-5747. https://doi.org/10.59429/ace.v8i3.5747
90. Dhamdhere P, Dixit SM, Tatiya M, Shinde BA, Deone J, Kaulage A, et al. AI-based monitoring and management in smart aquaculture for ocean fish farming systems. Appl Chem Eng. 2025 Sep 17;8(3):ACE-5746. https://doi.org/10.59429/ace.v8i3.5746
91. Keloth Kaithari D, Ayyappadas MT, Goel S, Shahin A, Patil SK, Chaudhari SS, et al. A review on GA-NN based control strategies for floating solar-ocean hybrid energy platforms. Appl Chem Eng. 2025 Sep 15;8(3):ACE-5745. https://doi.org/10.59429/ace.v8i3.5745
92. Bhambare PS, Kaulage A, Darade MM, Murali G, Dixit SM, Vali PSNM, et al. Artificial intelligence for sustainable environmental management in the mining sector: a review. Appl Chem Eng. 2025 Sep 18;8(3):ACE-5756. https://doi.org/10.59429/ace.v8i3.5756
93. Dharmadhikari DD, Ray A, Shinde BA, Raut SV, Taware RD, Desai S, et al. Machine learning applications in ore grade estimation and blending optimization for modern mining. Appl Chem Eng. 2025 Nov 6;8(4):ACE-5790. https://doi.org/10.59429/ace.v8i4.5790
94. Tatiya M, Darade MM, Shinde BA, Kumbhare MP, Taware RD, Chougule SM, et al. AI applications in tailings and waste management: improving safety, recycling, and water utilization. Appl Chem Eng. 2025 Nov 5;8(4):ACE-5789. https://doi.org/10.59429/ace.v8i4.5789
95. Upadhe SN, Mhamane SC, Kurhade AS, Bapat PV, Dhavale DB, Kore LJ. Water saving and hygienic faucet for public places in developing countries. In: Techno-Societal 2018: Proceedings of the 2nd International Conference on Advanced Technologies for Societal Applications. Vol 1. Cham: Springer; 2019. p. 617-24. https://doi.org/10.1007/978-3-030-16848-3_56
96. Kurhade AS, Siraskar GD, Darade MM, Dhumal JR, Kardile CS, Biradar R, Patil SP, Waware SY. Predicting heat transfer enhancement with twisted tape inserts using fuzzy logic techniques in heat exchangers. J Mines Met Fuels. 2024;72(7):743-50. https://doi.org/10.18311/jmmf/2024/45348
97. Kurhade AS, Siraskar GD, Kondhalkar GE, Darade MM, Yadav RS, Biradar R, Waware SY, Charwad GA. Optimizing aerofoil design: a comprehensive analysis of aerodynamic efficiency through CFD simulations and wind tunnel experiments. J Mines Met Fuels. 2024;72(7):713-24. https://doi.org/10.18311/jmmf/2024/45361
98. Kurhade AS, Kadam AA, Biradar R, Bhambare PS, Gadekar T, Patil P, Yadav RS, Waware SY. Experimental investigation of heat transfer from symmetric and asymmetric IC chips mounted on the SMPS board with and without PCM. J Adv Res Fluid Mech Therm Sci. 2024;121(1):137-47. https://doi.org/10.37934/arfmts.121.1.137147
99. Kurhade AS, Siraskar GD, Bhambare PS, Dixit SM, Waware SY. Numerical investigation on the influence of substrate board thermal conductivity on electronic component temperature regulation. J Adv Res Numer Heat Trans. 2024;23(1):28-37. https://doi.org/10.37934/arnht.23.1.2837
100. Kurhade AS, Waware SY, Munde KH, Biradar R, Yadav RS, Patil P, Patil VN, Dalvi SA. Performance of solar collector using recycled aluminum cans for drying. J Mines Met Fuels. 2024 May 1;72(5). https://doi.org/10.18311/jmmf/2024/44643
101. Kurhade AS, Kardekar NB, Bhambare PS, Waware SY, Yadav RS, Pawar P, Kirpekar S. A comprehensive review of electronic cooling technologies in harsh field environments: obstacles, progress, and prospects. J Mines Met Fuels. 2024;72(6):557-79. https://doi.org/10.18311/jmmf/2024/45212
102. Kurhade AS, Waware SY, Bhambare PS, Biradar R, Yadav RS, Patil VN. A comprehensive study on Calophyllum inophyllum biodiesel and dimethyl carbonate blends: performance optimization and emission control in diesel engines. J Mines Met Fuels. 2024;72(5):499-507. https://doi.org/10.18311/jmmf/2024/45188
103. Kurhade AS, Biradar R, Yadav RS, Patil P, Kardekar NB, Waware SY, Munde KH, Nimbalkar AG, Murali G. Predictive placement of IC chips using ANN-GA approach for efficient thermal cooling. J Adv Res Fluid Mech Therm Sci. 2024;118(2):137-47. https://doi.org/10.37934/arfmts.118.2.137147
104. Waware SY, Chougule SM, Yadav RS, Biradar R, Patil P, Munde KH, Kardekar NB, Nimbalkar AG, Kurhade AS, Murali G, Kore SS. A comprehensive evaluation of recent studies investigating nanofluids utilization in heat exchangers. J Adv Res Fluid Mech Therm Sci. 2024;119(2):160-72. https://doi.org/10.37934/arfmts.119.2.160172
105. Kurhade AS, Murali G, Rao TV. CFD approach for thermal management to enhance the reliability of IC chips. Int J Eng Trends Technol. 2022;71(3):65-72. https://doi.org/10.14445/22315381/IJETT-V71I3P208

106. Kurhade AS, Rao TV, Mathew VK, Patil NG. Effect of thermal conductivity of substrate board for temperature control of electronic components: a numerical study. Int J Mod Phys C. 2021 Oct 26;32(10):2150132. https://doi.org/10.1142/S0129183121501321
107. Waware SY, Kore SS, Kurhade AS, Patil SP. Innovative heat transfer enhancement in tubular heat exchanger: an experimental investigation with minijet impingement. J Adv Res Fluid Mech Therm Sci. 2024;116(2):51-8. https://doi.org/10.37934/arfmts.116.2.5158
108. Kurhade AS, Murali G. Thermal control of IC chips using phase change material: a CFD investigation. Int J Mod Phys C. 2022 Dec 28;33(12):2250159. https://doi.org/10.1142/S0129183122501595
109. Rami Reddy S, Murali G, Dhana Raju V. Assessment of diethyl ether as a fuel additive on diesel engine characteristics powered with waste mango seed biodiesel blend. Int J Ambient Energy. 2022 Dec 31;43(1):3365-76. https://doi.org/10.1080/01430750.2020.1824944
110. Emeema J, Murali G, Reddi BV, Mangesh VL. Investigations on paraffin wax/CQD composite phase change material: improved latent heat and thermal stability. J Energy Storage. 2024 Apr 30;85:111056. https://doi.org/10.1016/j.est.2024.111056
111. Rami Reddy S, Murali G, Dhana Raju V. Influence of decanol as fuel additive on characteristics of diesel engine powered with mango seed biodiesel blend. Int J Ambient Energy. 2022 Dec 31;43(1):2875-88. https://doi.org/10.1080/01430750.2020.1783356
112. Tamiloli N, Venkatesan J, Murali G, Kodali SP, Sampath Kumar T, Arunkumar MP. Optimization of end milling on Al-SiC-fly ash metal matrix composite using TOPSIS and fuzzy logic. SN Appl Sci. 2019;1(10):1204. https://doi.org/10.1007/s42452-019-1191-z
113. S. Manjula Gandhi, S. Sugumaran, N. Alangudi Balaji, Govindarajan Murali, Amruta Kundalik Mule, Harish Velingkar, et al. Artificial Intelligence in Predictive Toxicology: Modelling Xenobiotic Interactions and Human Risk Assessment. Appl. Chem. Eng. 2025 Dec. 17; 8(4):ACE-5826. https://doi.org/10.59429/ace.v8i4.5826.
114. Manjusha Tatiya, Babaso A. Shinde, Navnath B. Pokale, Mahesh Sarada, Mahesh M. Bulhe, Govindrajan Murali, et al. AI-Driven Process Control for Enhancing Safety and Efficiency in Oil Refining. Appl. Chem. Eng. 2025 Nov. 24;8(4):ACE-5792. https://doi.org/10.59429/ace.v8i4.5792
115. Ramdas Biradar, Babaso A. Shinde, Milind Manikrao Darade, Tushar Gaikwad, Seeram Srinivasa Rao, Aarti Puri, et al. AI Applications in Smart Mineral Processing: Ore Characterization, Sorting, and Efficiency. Appl. Chem. Eng. 2025 Nov. 24 ;8(4):ACE-5791. https://doi.org/10.59429/ace.v8i4.5791
116. Pallavi Vishnu Kharat, Beena Nawghare, N. Alangudi Balaji, Vishvas V. Kalunge, Charu P. Kumbhare, Tejasvini Rahul Katkar, et al. Data-Driven Prediction of Biofuel Yield and Combustion Emissions Using AI Techniques. Appl. Chem. Eng. 2025 Dec. 25;8(4): ACE-5841. https://doi.org/10.59429/ace.v8i4.5841
117. Swapnil S. Chaudhari, Kundan Kale, Manisha Raghuvanshi, Torana Kamble, Ramsing Thakur, Sagar Arjun Dalvi, et al. Machine learning for waste-to-energy processes: Resource evaluation, conversion efficiency, and environmental effects. Appl. Chem. Eng. 2026 Jan. 6 ;9(1): ACE-5850. https://doi.org/10.59429/ace.v9i1.5850
118. Madhuri Karad, Nidhi Sharma, Khaja Gulam Hussain, Vakiti Sreelatha Reddy, Madhuri Ghuge, Sagar Arjun Dalvi, et al. AI-Based Pollution Monitoring in Bio-Energy Production Chains: Methods, Applications, and Gaps. Appl. Chem. Eng. 2026 Jan. 6 ;9(1): ACE-5848. https://doi.org/10.59429/ace.v9i1.5848
119. Smita Desai, Sushama Shirke, Vishvas V. Kalunge, Sireesha Koneru, Gaurav Raju Khobragade, Vidhi Rajendra Kadam, et al. Machine Learning Approaches for Biomass Resource Mapping and Sustainable Energy Planning. Appl. Chem. Eng. 2025 Dec. 29; 9(1): ACE-5843. https://doi.org/10.59429/ace.v9i1.5843
120. Madhuri Karad, Puja Gholap, Ashwini Dhumal, Vilas Suresh Mane, N. Alangudi Balaji, Kunal Ingole, et al. AI Models for Life-Cycle Assessment of Bio-Energy Technologies and Pollution Quantification. Appl. Chem. Eng. [Internet]. 2026 Jan. 20 [cited 2026 Feb. 3];9(1):ACE-5855. https://doi.org/10.59429/ace.v9i1.5855
121. Waware SY, Bote MA, Patil SP, Biradar R, Katke G, Kadam AA, Ghunake KB, Kore SS, Murali G, Kurhade AS. Artificial Intelligence in Extractive and Processing Industries: Applications Across Mining, Metallurgy, and Petroleum Sectors. NIPES-Journal of Science and Technology Research. 2025 Dec 14;7(4):196-208. https://doi.org/10.37933/nipes/7.4.2025.1740
122. Waware SY, Nagalli NK, Sugumaran S, Patil PD, Biradar R, Kadam AA, Ghunake KB, Kore SS, Murali G, Kurhade AS. AI-Driven Innovations in the Exploration, Extraction, and Processing of Minerals, Metals, and Petroleum: A Review. NIPES-Journal of Science and Technology Research. 2025 Dec 14;7(4):209-27. https://doi.org/10.37933/nipes/7.4.2025.1717