Integrating AI and IoT in Advanced Optical Systems for Sustainable Energy and Environment Monitoring

Shamim Ahmad khan[1], Dr. Abdul Hameed Kalifullah[2], Kamila Ibragimova[3],
Dr. Akhilesh Kumar Singh[4], Elangovan Muniyandy[5], Venubabu Rachapudi[6]

Research Scholar, Glocal School of Science and Technology, Glocal University, Uttar Pradesh, India[1]
Assistant Professor, Department of Marine Engineering and Nautical Sciences,
National University of Science and Technology (IMCO), Sohar, North Batinah, Oman[2]
Department of Computer Engineering, Tashkent University of Information Technologies, Uzbekistan[3]
Professor, Department of Mechanical Engineering, Aditya College of Engineering, Surampalem, Andhra Pradesh, India[4]
Department of Biosciences, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences,
Chennai, India[5]
Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation,
Vaddeswaram, Guntur, Andhra Pradesh, India[6]

***Abstract*—The increasing demand for sustainable energy solutions and environmental monitoring necessitates advanced technologies. This work combines the capabilities of AI, in the form of a GRU-Auto encoder, with IoT-connected Advanced Optical Systems to create a comprehensive monitoring system. Current monitoring systems often face limitations in real-time analysis and adaptability. Conventional methods struggle to provide timely insights for sustainable energy and environmental management due to the complexity of data patterns and the lack of dynamic adaptability. Our proposed methodology introduces an optimized GRU-Auto encoder, which excels in learning complex temporal patterns, making it well-suited for dynamic environmental and energy data. The integration with Advanced Optical Systems ensures a continuous influx of high-quality real-time data through IoT, enabling more accurate and adaptive analysis. The study involves optimizing the GRU-Auto encoder through hyper parameter tuning and gradient clipping. The model is integrated into an IoT platform that connects with Advanced Optical Systems for seamless data flow. Real-time data from environmental and energy sensors are processed through the AI model, providing immediate insights. Performance is evaluated based on the system's ability to accurately predict environmental trends, optimize energy consumption, and adapt to dynamic changes. Comparative analyses with traditional methods show advantages of the suggested strategy in terms of efficiency and accuracy. This research presents a significant development in the field of study of sustainable energy and environment monitoring, offering a robust solution for real-time data analysis and adaptive decision-making. The integration of an optimized GRU-Auto encoder with IoT-connected Advanced Optical Systems showcases promising results in improving overall system performance and sustainability.**

Keywords*—Auto encoder; artificial intelligence; Internet of Things; gated recurrent unit; sustainable energy; environmental monitoring

I. Introduction

Pollutants that degrade the natural environment pose a major hazard to the environment and the well-being of humans. Human activities such as mineral extraction, fast urbanization, industrialization, and unregulated development of resources from nature are regarded as the primary causes of worldwide environmental contamination Tripathy et al. [1]. Synthetic microfiber pollution caused by the home laundry of synthetic clothes has recently been identified as an important cause of synthetic micro plastic contamination in the marine environment using several monitoring methods [2]. These are fine, soft, lightweight luxury fibres created from synthetic or natural fibres that are used for a large number of tasks ranging from industrial filtration to household cleaning [3]. Microfibers are comprised of polypropylene, polyamide (nylon), and polyethylene terephthalate; thus they are porosity and dry, making them great for cleansing. The widespread usage of synthetic microfibers in all industries has resulted in the build-up of microfibers trash in both soil and maritime environments, posing a significant hazard to the environment today and in years to come [4]. Microfibers are a serious marine contaminant because of their durability, ubiquity, and synthetic nature.

The overuse of petroleum and coal has caused global warming and serious environmental contamination. Electronic devices and wireless sensor networks that track the surrounding environment need conventional sources of power like cells and electrical wire nets [5]. Yet, typical sources of power for WSNs have drawbacks, such as complicated wiring, short lives, difficult servicing and repair in remote regions, and possible pollution of the environment. Considering these factors, scientists are frantically looking into other renewable energy sources like wind, solar power, heat, and water waves. Wind is regarded as one of the most important energy sources. It has various advantages, including high energy capability, frequent and prevalent presence in nature, and eco-friendliness [6]. Typical wind energy harvesting requires huge dimensions and quantities, distant sites, and high manufacture and construction expenses, limiting its use to autonomous WSNs. As a result, scientists are working to miniaturise wind-powered generators for autonomous WSNs in real-world applications [7]. The wind energy generated by running trains and automobiles in tunnels and adjacent tube lines may be captured and utilized to power self-contained environmental monitoring devices. There is a high need for power to illuminate extensive tunnels for safety reasons [8]. In addition, lit posters and dynamic LED displays for passengers may be fascinating uses to be driven by the generated flowing wind in subways lines and man-made tunnels.

With the rapid growth of industry and agriculture, along with the widespread use of synthetic medications in human life, the water, air, and the planet's environments have been contaminated by a variety of toxic pollutants, including heavy-metal ions, organic substances, dyes, drugs, chemicals, bacteria, viruses, gases, and others [9]. The presence of even trace amounts of toxicity can endanger the environment and cause irreparable harm to individuals. As a result, the rapid, actual time, sensitive, and specific detection of harmful contaminants in natural habitats became critical. Conventional bioanalysis methods, like UV-vis spectroscopy, high-efficiency liquid chromatography-mass spectrometry, atom absorption spectroscopy, and more, have been extensively used to determine a variety of substances, and analytical substances with extremely low concentrations have been successfully detected [10]. These devices are costly and require sophisticated operation. Furthermore, finding it is time-consuming. These restrictions limited the extensive use of the aforementioned methodologies for easy, rapid, and reliable bioanalysis and identification of diverse toxins [11].

Air pollution harms the well-being of people and is seen as a major worldwide concern, particularly in nations where the gas and oil sectors are prevalent. The main objective of environmental monitoring isn't just to collect data from multiple positions, but also to supply researchers, developers, and legislators with the data they need to make decisions about how to handle and enhance the environment, as well as to present useful data to end users. Air pollution in India is a serious health issue [12]. Based on a 2016 study, at least 140 million people in India inhale air that is 10 times or greater filthy above the WHO tolerable limitation, and India is host to 13 of the globe's 20 cities with the lowest annual pollutant levels. Pollution from industries accounts for 51% of total pollution, followed by cars (27%), agricultural burning (17%), and fireworks (5%). Every year, air pollution causes two million premature mortalities in India. Thus, it is vital to monitor environmental conditions and reduce air pollution. Researchers use a temperature and humidity sensor to determine the temperature and humidity of the atmosphere, which helps us anticipate environmental conditions [13]. The MQ7 sensor detects carbon monoxide in the surroundings, whereas the MQ135 monitors air quality. The server keeps and displays the present values for each of the four variables. A lookup database is created that contains an array of moisture and temperature and is used to anticipate the present climate. For instance, if the humidity is high while temperature is low, the likelihood of rain increases.

The study aims to solve the developing issues of monitoring and controlling sustainable energy and environmental factors by offering an innovative combination of AI and the IoT in the field of Advanced Optical Systems. The widespread use of Advanced Optical Systems, which include advanced environmental detectors and energy monitoring equipment, has paved the way for a thorough awareness of our surroundings. However current monitoring approaches have significant drawbacks concerning real-time analysis, flexibility to variable modifications to the environment, and the sophisticated processing of the complicated temporal patterns associated with gathered data. To address these gaps, we provide a cutting-edge method that makes use of a GRU-Autoencoder. The GRU-Autoencoder, selected for its ability to capture complicated temporal correlations within data, is optimized through thorough parameter adjustment. This AI model is at the heart of our methodology, providing a solid platform for real-time, adaptive evaluation of environmental and energy data. The research goes beyond AI innovation and embraces the Internet of Things concept. Advanced Optical Systems are completely connected with an IoT platform, creating a network for safe and efficient communication. This connectivity not only provides continuous data flow, but also enables the development of an evolving system that can adapt to changing environmental circumstances. The fundamental aims of this study derive from the complex interplay of AI, IoT, and Advanced Optical Systems: to improve the precision and effectiveness of sustainable energy and environmental monitoring. This work contributes to the increasing body of knowledge in the sector, providing a potential pathway for the creation of adaptive systems that can usher in a new era of sustainable resource management. We want to illustrate our approach's disruptive potential by thoroughly examining the suggested methodology, which includes model optimization, data processing, IoT integration, and actual time performance evaluation. The findings of this study have ramifications for a wide range of industries, from energy generation and use optimization to active environmental leadership, laying the path for a more resilient and environmentally friendly future. The key findings from this study are as follows:

- Presents an innovative integration architecture that integrates a GRU-Auto encoder with Advanced Optical Systems and the IoT for sustainable energy and environmental monitoring.
- Improves the GRU-Auto encoder’s efficiency using rigorous optimization strategies, such as hyper parameters tweaking, to collect and analyse complicated temporal trends in real-time data.
- Integrates Advanced Optical Systems seamlessly with an IoT platform, guaranteeing safe and efficient connection, ongoing information flow, and flexibility to adapt in ambient circumstances.
- Real-time transfer of information from gadgets connected to the Internet of Things to the artificial intelligence algorithm allows for adaptive study of environmental changes and dynamic energy usage patterns.
- Helps the progress of sustainable management of resources by offering precise information about environmental trends, optimizing energy usage, and encouraging educated making decisions for a healthier future.

The study, which begins with a detailed literature analysis in Section II, sheds light on the present state of AI, IoT, and optical systems in sustainable energy and environmental monitoring. Section III summarises the issue statement, noting the limits of standard monitoring systems and proposing a creative integrated solution. Section IV discusses the study approach, which includes data collecting, system design, AI algorithm development, and rigorous testing processes. Section V summarises the study's findings, demonstrating the usefulness of the integrated system through performance assessments. Section VI dives into topics, including ramifications, methodological comparisons, and prospective applications. Section VII is a detailed conclusion that summarises significant findings and the transformational potential of the combined AI and IoT method for developing sustainable energy and environmental monitoring techniques.

II. Related Works

Ullo et al. [14] explains that Air quality, water pollution, and radiation contamination are significant environmental issues. Appropriate monitoring is essential so that the globe may attain sustainable development while preserving a healthy society. With advancements in IoT and the introduction of sophisticated sensors, environmental monitoring has evolved into a smart environmental monitoring (SEM) system. Given this context, the current publication attempts to conduct an in-depth evaluation of important developments and study works on SEM, including monitoring of air and water quality, radioactive pollution, and agricultural systems. The examination is structured around the aims for which SEM methods are utilized, and every purpose is then analysed based on the sensors utilised, machine learning methods used, and classification approaches used. The comprehensive analysis followed an exhaustive study that made crucial recommendations and implications for SEM research based on conversations regarding results and study patterns. The authors looked at advances in sensor technology, IoT, and machine learning technologies might convert environmental monitoring into a truly smart monitoring system. A method based on powerful machine learning methods, denoising techniques, and the construction of acceptable norms for wireless sensor networks (WSNs) is being developed. One possible disadvantage is the extended scope, since researching other elements such as sound pollution and catastrophes may raise the level of difficulty and financial requirements of the study.

The population has grown dramatically in recent decades, as has socioeconomic progress. In terms of environmental change caused by societal and economic growth, the maritime environment has a substantial impact on global climate change. As a result, current communications and information technicians are interested in monitoring the maritime environment. Several maritime monitoring systems have been developed in recent years. The Internet of Things is particularly important in this regard. IoT-based maritime surveillance systems, many sensors are used in real-time to track and measure numerous physical factors. These sensors operate on battery power. When the battery empties, monitoring action may be interrupted till the batteries is replaced. Reddy et al. [15] focuses on establishing a system of predictions for forecasting the battery's lifespan in advance of time and alerting technicians so that surveillance is not stopped, utilising Principal Component Analysis (PCA) and Deep Neural Network (DNN). The method is assessed utilising raw data acquired from a real-time coastal monitoring system located along the Chicago Park District's beach water. The collected findings are contrasted and evaluated using two frequently utilised state-of-the-art methods: Linear Regression and XGBoost. The findings reveal that the suggested PCA-based DNN Predictions Model beats the other strategies by 12% in correctness and 30% in reduced time complexity. Using the suggested forecasting framework to different real-time IoT networks may bring hurdles in terms of adjusting the method to varied network designs, and evaluating the influence of the bio-inspired method on decreasing dimensionality might entail new computing complications.

Okafor et al. [16] explains that the present growth in global climate change issues has made environmental monitoring an important study subject. Existing environmental monitoring systems, on the other hand, are expensive to acquire and hard to implement, needing substantial resources, facilities and experience. It is unable to produce with these methods high density within-situ networks, like those necessary to develop finer scale simulations to support robust monitoring, resulting in huge gaps in the acquired dataset. Low-Cost Sensors may provide high-resolution spatiotemporal metrics that can be utilised to enhance current environmental surveillance datasets. LCS, on the other hand, require periodic correction for them to produce accurate and trustworthy data because they are typically influenced by surroundings when installed in the field. Calculating LCS can assist enhance data quality and assure correct data collection. But successful validation necessitates recognising variables that influence sensor quality of data for a specific measurement. The current study compares the efficacy of three features selection algorithms, namely Forward Feature Selection, Backward Elimination (BE), and Exhaustive Feature Selection, to identify parameters that impact the data dependability of low-cost connected gadget sensors used to monitor environmental systems. Using the information fusion technique, sensor data was merged with environmental characteristics to create a single validation equation for evaluating sensors using Linear Regression and Artificial Neural Networks. The research found that calibration may increase the value of low-cost IoT sensor data, and it can also make choosing features and data fusing easier, resulting in more dependable, precise, and trustworthy data for calibrating systems. The study found that the cairclipO3/NO2 sensor offered readings that had a significant relationship with prior measures, whereas the cairclipNO2 sensor showed no relevant link with the source information.

Coulby et al. [17] Monitoring indoor environmental quality (IEQ) is becoming increasingly important for well-being as well as health. New building regulations, climate objectives, and the introduction of work-from-home practices are driving demand for flexible monitoring systems with onward Cloud connection. Affordable Micro-Electromechanical Systems (MEMS) sensors can meet these objectives, allowing for the creation of customized multifunctional devices. Researchers report findings from the creation of MEMS-based IoT-enabled multifunctional devices for IEQ tracking. Research was carried out to determine inter-device variation and validity against benchmark sensors/devices. For the multifunctional IEQ track, interclass relations and Bland-Altman studies showed strong inter-sensor consistency and excellent agreement for the majority of sensors. All affordable sensors were shown to be responsive to environmental changes. Numerous sensors indicated poor accuracy with high precision, indicating that they might be corrected using reference devices to improve accuracy. The multimodal devices created here was shown to be suitable for its intended function of giving general signs of environmental changes for ongoing IEQ monitoring. However, increasing the installation of the multifunctional device for ongoing surveillance may pose logistic and operational problems that must be handled with care in practical applications.

Kashid et al. [18] explains that Nowadays, environmental preservation is critical for humans to ensure secure and prosperous living. Tracking requirements vary greatly, depending on geography and expanding to specialized uses that require flexibility. The suggested system describes the deployment of an IoT that may evolve into a variety of programs and has the versatility necessary to exchange and improve without the need to systematize complex equipment. The solution is essentially built on independent Wi-Fi sensor nodes, tiny Wi-Fi receivers connected to the internet, and a cloud architecture that provides data storage and transit to remote customers. The solution enables administrators at home to not only monitor the current situation on their mobile phones but also expose remote Internet Websites. All evaluations are kept at various stages to enable secure conformance and accessibility to preserved information in the case of a group breakdown or reachability. The suggested gadget is useful for monitoring temperature, humidity, and other parameters. This value is predicted using machine learning approaches like regression and editing. Pre-data processing is necessary for removing the data through error rate, verification of information, and so on. Machine learning algorithms are extremely strong and accurate when working with data predictions.

In the last few years, environmental monitoring has grown into an SEM system, making use of improvements in IoT, sensor technology, and machine learning. Studies, such as those done by Ullo et al., emphasize the need to monitor air quality, quality of water, radiations contamination, and agricultural systems for environmentally friendly growth. Yet, the inclusion of other elements such as noise pollution and catastrophes in SEM study may present difficulties. Reddy et al. offer by creating a method for forecasting the charge life of IoT-based maritime monitoring devices, which improves continuous monitoring. Although the suggested model beats previous strategies, it may be difficult to adapt to different real-time IoT networks. Okafor et al. tackle the expense and complicated nature of environmental monitoring systems by investigating sensors with low prices and testing choosing features methods for validation. The research reveals how calibration may improve data quality, especially for certain sensors. Coulby et al., on the other hand, focus on the quality of indoor environment monitoring utilizing MEMS-based IoT-enabled multimodal devices, emphasizing its dependability while admitting scaling limitations. Kashid et al. provide a system based on the IoT for environmental monitoring that emphasizes flexibility and simplicity of installation. The system stores and transports data using Wi-Fi node sensors and a cloud platform. Machine learning approaches are used to forecast variables such as temperature and humidity, demonstrating the system's accuracy. In general, these investigations provide helpful insight into the problems, improvements, and possible downsides in the area of environmental monitoring, emphasizing the need for constant creativity and adaptability in the context of new technology.

III. Problem Statement

Despite the advances in EMS highlighted in the papers, problems remain. One disadvantage is the possible difficulty of converting IoT-based marine monitoring models to various real-time IoT networks, which limits their general application. Furthermore, the scalability limits in MEMS-based IoT-enabled interior environment monitoring devices emphasize the difficulty in expanding the dependability of such systems to greater scales. Existing methods may fail to offer timely, smart, and precise tracking of energy use, emissions, and environmental factors [19]. The lack of a seamless connection between AI and IoT technologies impedes the creation of a comprehensive solution for effective and sustainable monitoring procedures. The originality of this research resides in solving the constraints associated with existing environmental monitoring devices by proposing an extensive approach that incorporates AI and IoT into Advanced Optical Systems. Traditional monitoring systems sometimes suffer from immediate evaluation and flexibility, which limits their usefulness in sustainable energy and environmental management. The suggested solution solves these issues by employing an optimized GRU-Auto encoder, which is well-known for its ability to learn complicated temporal patterns. This unique AI model is optimized for changing environmental and energy data, increasing the systems adaptively. The combination of Advanced Optical Systems and IoT allows for a constant and high-quality stream of real-time data, resulting in more precise and adaptable assessments. By merging cutting-edge AI skills with IoT connection and overcoming the limits of traditional approaches, we can considerably improve the area of sustainable energy and environmental monitoring.

IV. Integrating AI and IoT for Sustainable Energy and Environment Monitoring

The study technique includes defining the scope by identifying difficulties in current sustainable energy and environmental monitoring systems. The study's basic AI model is a GRU-Auto encoder, which is optimized for efficiency using hyper parameter tweaking. Different data from Advanced Optical Systems, including environmental sensors and energy monitoring devices, undergo rigorous pre-processing. Integration with IoT allows for safe connectivity and immediate information transfer to the GRU-Auto encoder. The process closes with a thorough performance evaluation, applying specific criteria to measure the system's accuracy in anticipating environmental trends and optimizing energy use, providing important conclusions for sustainable resource management. Fig. 1 explains the overall conceptual diagram.

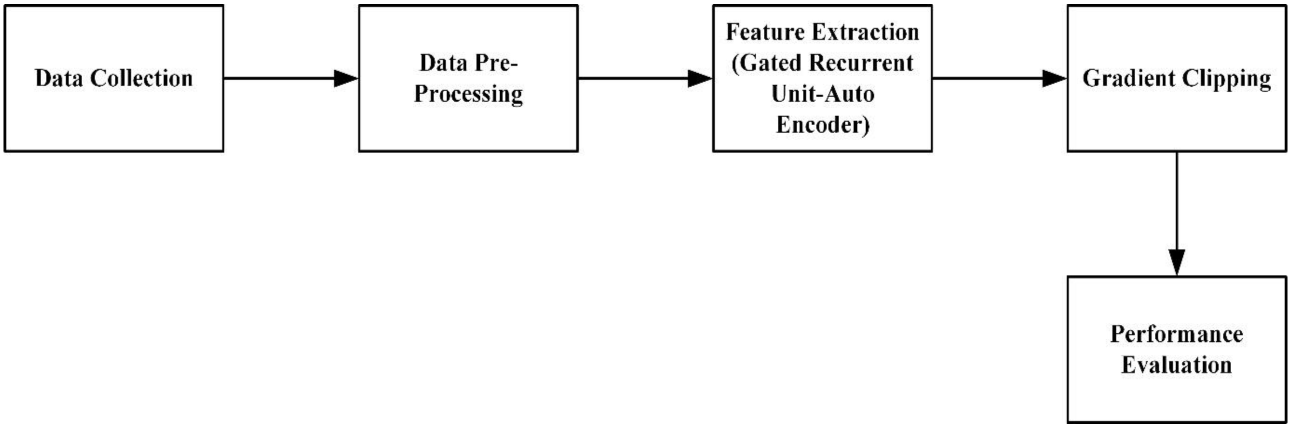

Fig. 1. Conceptual diagram.

A. Data Collection

The data was collected from three identical, made specifically sensor arrays. Every array was linked to a Raspberry Pi device. All of these three IoT gadgets were installed in a real location with varying environmental conditions. Each IoT device gathered seven distinct values from all four sensors at regular times. Sensor outputs include smoke, temperature, CO, humidity, sunlight, LPG, and motion. The information ranges from 07/12/2020 00:00:00 UTC to 07/19/2020 23:59:59 UTC. There are 405,184 rows of information. The sensor values, together with a unique device ID and date, have been transmitted as a single message, utilizing the ISO standard Message Queuing and Telemetry Transport (MQTT) networking protocol [20]. Table I depicts the dataset criteria.

TABLE I. DATASET DESCRIPTION

Device	Humidity	Light	Motion	Smoke	Temp
b8:27: eb:bf:9d:51	51.0	False	False	0.020411	22.7
00:0f: 00:70:91:0a	76.0	False	False	0.013275	19.700001
b8:27: eb:bf:9d:51	50.9	False	False	0.020475	22.6
1c:bf: ce:15:ec:4d	76.800003	True	False	0.018628	27.0

B. Data Pre-processing

The data preliminary processing layers are positioned in the heart of the IoT systems topologies, allowing raw data's to be collected and pre-processed utilising contemporary data mining techniques. It also finishes information collection or breakdown, data cleaning, matching or assessment, sharing as appropriate, and occasionally triggers alarms or warnings depending on established standards.

C. Data Cleaning

Data is filthy when a large amount of inaccurate data (e.g., instrument failure, communication error, and human or computer mistake) is discovered in the actual world. The acquired data may be partial, missing key features of interest or value, noisy, and inconsistent, with errors in codes or names. In this study, unfinished (missing data) and noise are considered into account.

D. GRU-Auto Encoder

As a model for deep learning, RNN uses a structure known as loops to gather temporal information from the input sequences. GRU and LSTM networks are two examples of upgraded RNNs that can successfully gather time-based information while also addressing the gradient disappearing problem. Compared to LSTM, the GRU network has reduced training variables, resulting in improved training efficiencies at comparable accuracy. Thus, the GRU networks are used in the present research to extract and merge the temporal aspects of the input information. Fig. 2 depicts the basic GRU construction, which comprises of update gate z and reset gate r. The update gate z represents the number of information transmitted from the hidden state that was previously present to the present time point, whereas the reset gate r determines whether it ignores the prior hidden state. Eq. (1) describes the operation of each GRU, with the hidden state h representing the secret time data recovered by every unit [21].

$$H^{t1} = f(H^{t1-1}, x_{(t)}) \tag{1}$$

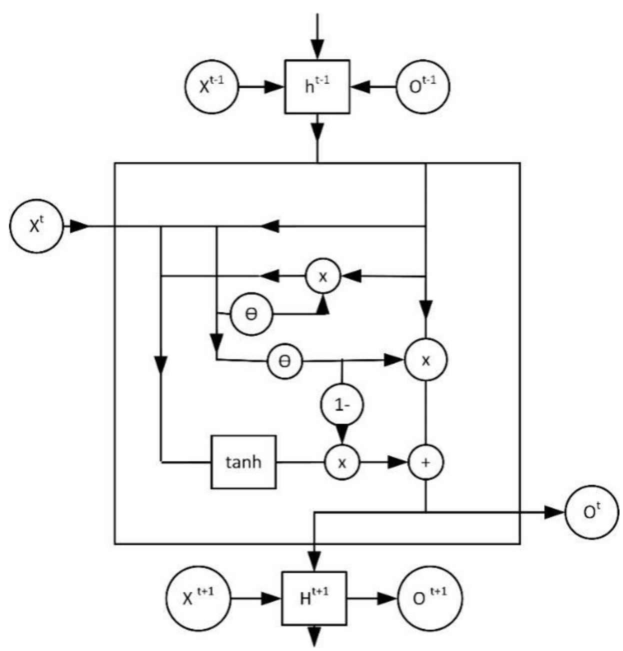

Fig. 2. GRU Architecture.

where, H^{t1-1} and H^{t1} represent the hidden states at time t-1 and time t, respectively, while $x_{(t)}$ signifies the input series of data at time t. Therefore, the reset gate r and the gate for updating z may be determined as follows in Eq. (2) and Eq. (3):

$$r^t = \sigma(W^r x_{(t)} + U^r h^{t-1} + b^r) \tag{2}$$

$$z^t = \sigma(W^z x_{(t)} + U^z h^{t-1} + b^z) \tag{3}$$

$\boldsymbol{\sigma}$ is the exponentially activating equation, whileW^r,W^z,U^r, and U^z are the adaptive coefficient matrices. b^r and b^z indicate the bias. The concealed state at that point can be reconstructed in Eq. (4) and Eq. (5):

$$H^{t1} = (1 - z^t) \odot H^{t1-1} + z^t \odot H^{t1} \tag{4}$$

$$\widetilde{H}^{t1} = \tanh(W^v x^{(t)} + U^v(r^t \odot H^{t1-1}) + b^v) \tag{5}$$

where, W^v and U^v are the adaptable Coefficient matrix and b^v is the bias [21].

The collection of M sensors (also known as data generators), marked $\{m^1, \ldots, m^{\mathrm{M}}\}$, are employed to record the behaviour of the turbo compressor. Each sensor m^i provides a vibration observing sequence $x^i = (x_1^i,\ x_2^i\ , \ldots)$. The data generator $m^i{}_{i\in\{1\ldots\mathrm{M}\}}$ is modeled with an LSTM-based autoencoder AE^i that is trained by continuous gradient descent to minimize the reconstruction error term among the initial signal and the reconstructed one [22].

AEs are a nonlinear generalization of principal component analysis. They both fall under the category of unsupervised representational learning, which "tries to characterize the data-generating distributions through the identification of a set of characteristics or latent variables that vary to capture the majority of the framework of the data-generating distribution". These latent variables constitute the "information bottleneck" because of their small size, forcing the model to learn crucial properties from the initial signal. This occurs through a pair of processes: encoding and decoding, both based on the LSTM unit.

LSTM units are a strong sort of RNN that avoids the long-term dependency issue while memorizing information over time. The main element of these parts is the cell state, which is meant to maintain information over a period. At every interval t, information is introduced to and eliminated from this cell state using distinct gates: the forget gate f^t defines the degree to which data remains from earlier time-step; the input gate i^tt manages the movement of data from the present input x^t, and the gate that outputs the data o^tenables the framework to obtain data from the cell.

Informally, given a series of inputs x = $(x^{t_1}\ , \ldots, x^{t_2})$ between two predetermined t_1 and t_2, irrespective of the data generator, at every one time step, the present state of the cell c^t, and also the present secret state h^t, are calculated employing the prior cell state c^{t-1} and the present input sample in Eq. (6-11):

$$i^t = \sigma(W^{ii} x^t + b^{ii} + W^{hi} h^{t-1} + b^{hi}) \tag{6}$$

$$f^t = \sigma(W^{if} x^t + b^{if} + W^{hf} h^{t-1} + b^{hf}) \tag{7}$$

$$g^t = tanh(W^{ig} x^t + b^{ig} + W^{hg} h^{t-1} + b^{hg}) \tag{8}$$

$$o^t = \sigma(W^{io} x^t + b^{io} + W^{ho} h^{t-1} + b^{ho}) \tag{9}$$

$$c^t = f^t c^{t-1} + i^t g^t \tag{10}$$

$$h^t = o^t \tanh(c^t) \tag{11}$$

where, the matrix values W and b reflect its biases and weights. The subscripts correlate to the respective gates, such as W^{hi} for the hidden-input gates matrix and W^{io} for the inputs and outputs gate matrix. These are learned using gradient descent, whereas σ and $tanh$ are the logistic and hyperbolic tangent operations, accordingly, which are employed to inject irregularities within the model.

The first element encrypts a sequence of characters or a set of sequences with LSTM units and changes its hidden state by Eq. (1). They call this procedure h^t= LSTM (h^{t-1},x^t). The final hidden state has sufficient details regarding the framework of the entire input pattern that has been processed to retrieve the initial sequence through decoding [22]. Every generator is evaluated independently to provide an encoding c^{m^i} at the final time-step t_2 utilizing the previous hidden stateh^{t_2-1} as Eq.. (12):

$$c^{m^i} = LSTM(h^{t_2-1}, x^{t_2}) \tag{12}$$

To determine the behaviour of the generators m^i by including a set of associated ones $\{m^j\ |j\ \in\ J\}^{J\subseteq\{1,..,M\}}$, an encoder c^{m^J} is learned using the rest of the concatenation signals, and the secret state is thus modified as follows in Eq. (13).

$$c^{m^J} = LSTM(h^{t_2-1}, [x_j^t]_{j\in J}) \tag{13}$$

This encoded information is also known as context vectors, particularly in the area of machine transformation because they record the context, or significance, of a specific sequence of words.

This encoded information, which reflects the initial signal's reduced form, is used to track its restoration. At every time step, the decoder receives the encoded value c^{m^i} (or c^{m^J}) and both the ground truth example and the earlier reconstructed example. This is known as the teacher-forcing method, as opposed to the free-running option. Likewise, to the encoders, the state that is hidden (h^t) is modified in Eq. (14):

$$h^t = LSTM(h^{t-1}, y^{t-1}, c^{m^i}) \tag{14}$$

Let $y^i = (y_i^{t1}, \ldots y_i^{t2})$ be the auto encoder's results that correspond to the input pattern $x^i = (x_i^{t1}, \ldots x_i^{t2})$ of the information generator m^i got through a linear model of the hidden state. They characterize the total expense function J concerning x^i and the reconstructed y^i as the mean square error as Eq. (15).

$$MSE(x^i, y^i) = \frac{1}{t_2 - t_1} \sum_{t=t_1}^{t_2} (x_i^t - y_i^t)^2 \tag{15}$$

Forward and backward transmission of the errors in reconstruction among the decoder and encoder parts allows the framework to reduce the disparity between the initial signal and its reconstructed form and, in addition, results in a space of latent information (the encoding) which reflects important characteristics of the data distribution [22]. Fig. 3 shows the Architecture of Auto encoder.

Algorithm: GRU-Auto encoder for Sustainable Energy and Environment Monitoring.

1) Import and pre-process data.
2) Separate data into testing and training sets.
3) Normalise data.
4) Define the GRU-Auto encoder Architecture.
5) Compile the Model.
6) Train the GRU-Auto encoder.
7) Validate the model using the test set.
8) Save the Trained Model.

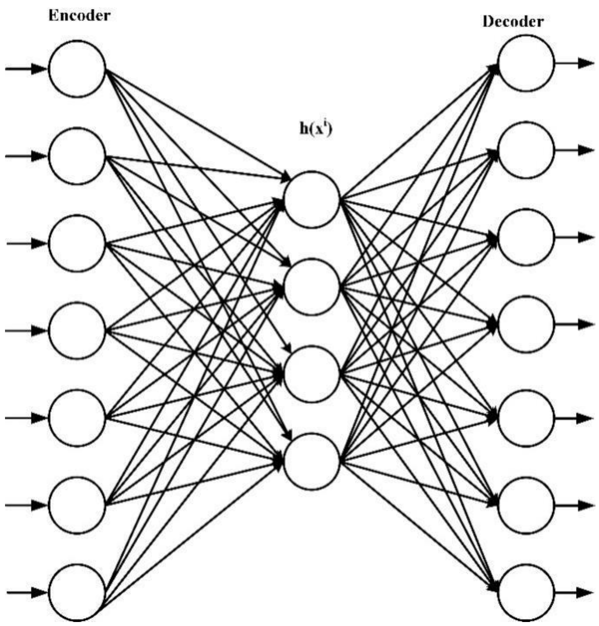

Fig. 3. Auto-Encoder architecture.

E. Gradient Clipping

The problem of ballooning gradients presents a substantial difficulty, particularly in deep architectures. This problem occurs when the distributions of the loss function grow overly big, resulting in unstable and divergence training. To address this issue, the gradient clipping approach uses a threshold setting. If the calculated gradient norm exceeds the threshold during backpropagation, the whole gradient vector is correspondingly scaled down to ensure that it does not exceed the limit. This precise control enhances the reliability of the training procedure, reducing the possibility of model divergence and allowing for smoother convergence. By carefully choosing the threshold and implementing gradient clipping, professionals improve the resilience of neural network training, especially in complicated circumstances where the bursting gradient issue may hamper progress. This approach is a key asset in the collection of tactics that focus on improving the dependability and efficacy of deep learning models.

F. Integration with IoT and Real-time Data Flow

During the implementation phase, Advanced Optical Systems are smoothly integrated into an IoT platform, resulting in a single environment for efficient data transmission. This connection is formed through the use of Application Programming Interfaces (APIs) or middleware, which allows for effective communication between Advanced Optical Systems and the IoT platform. Simultaneously, strong communication protocols like HTTPS are used to improve data security. This guarantees the encryption of the incorporated data during transmission, preventing unauthorized access. The ongoing real-time stream of information is then controlled via protocols such as MQTT, allowing for the constant transmission of secured information from devices connected to the Internet of Things to the GRU-Auto encoder This constant information flow, together with the flexibility inherent in the GRU-Auto encoder architecture, enables the model to stay in sync with changing environmental variables, resulting in real-time analysis and precise forecasting. The entire integration therefore establishes a safe, efficient, and adaptive platform for ongoing tracking and evaluation of environmental and energy data. This guarantees that the model receives frequent updates, enabling it to respond dynamically to alterations in environmental conditions. The integration of secure connectivity and real-time data flow creates a robust architecture, improving the GRU-Auto encoder's capacity to deliver accurate and adaptable analytics for sustainable energy and environmental monitoring.

Hyperparameter tuning is a crucial step in optimizing the performance of the GRU-AE model. Parameters like learning rate, batch size, number of layers, and hidden units are fine-tuned to enhance model efficiency and accuracy. This process typically involves techniques like grid search or random search, where various combinations of hyperparameters are tested to find the optimal configuration that minimizes loss and maximizes performance metrics. Gradient clipping is employed to address the issue of exploding gradients, which can destabilize training and lead to divergent behaviour. By setting a threshold value, gradient clipping limits the magnitude of gradients during backpropagation, ensuring that they do not grow excessively. This helps maintain stability in the training process, prevents the model from overshooting optimal parameters, and enables smoother convergence towards the global minimum of the loss function. As a result, gradient clipping enhances the reliability and efficiency of the GRU-AE model, improving its overall performance in capturing complex temporal patterns and producing accurate predictions.

V. RESULTS

This research successfully integrates AI and IoT in Advanced Optical Systems to address limitations in real-time analysis and adaptability within current sustainable energy and environmental monitoring systems. The proposed methodology introduces an optimized GRU-Auto encoder, proficient in learning complex temporal patterns, enhancing its suitability for dynamic environmental and energy data. The integration with Advanced Optical Systems, facilitated through IoT connectivity, ensures a continuous influx of high-quality real-time data, enabling more accurate and adaptive analysis. The study involves rigorous optimization of the GRU-Auto encoder through hyper parameter tuning and gradient clipping, with performance evaluation demonstrating superior efficiency and accuracy compared to traditional methods. This significant advancement in sustainable energy and environment monitoring offers a robust solution for real-time data analysis and adaptive decision-making, showcasing promising results in improving overall system performance and sustainability.

A. Performance Metrics

The assessment metrics are used to assess the environmental monitoring of GRU-AE. These are the Root Mean Square Error (RMSE) and Mean Absolute Error. Equations illustrate the computations for these three variables as shown in Eq. (16), and (17).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y^i - y_*^i)^2} \tag{16}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y^i - y_*^i\right| \tag{17}$$

TABLE II. AIR TEMPERATURE

Year	Air Temperature(°c)
2019	7.4
2020	8.5
2021	4.3
2022	5.2
2023	6.7

Table II shows the annual air temperatures (°C) from 2019 to 2023, with a variation from 4.3°C in 2021 to 8.5°C in 2020.

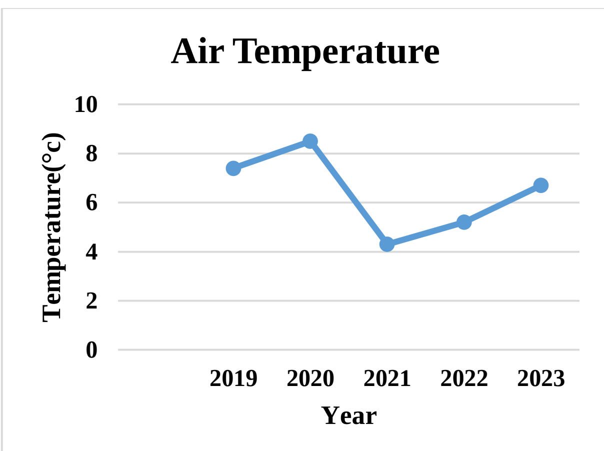

Fig. 4. Annual air temperature.

Fig. 4 depicts a line graph named Annual Air Temperature. The x-axis depicts the years 2019 through 2023. The y-axis shows the temperature in degrees Celsius, which ranges from 0 to 9. A line with circle marks represents the air temperatures for every year. In 2019, the air temperature was around 8°C. The temperature dropped significantly in 2020, falling to roughly 5°C. In 2021, it will drop to roughly 3°C. From then, it indicates an uptick; by 2023, it's back to roughly 5°C.

Table III shows the yearly relative humidity % for the years 2019 to 2023, which ranges from 5.1% in 2022 to 5.6% in 2020.

Fig. 5 shows a line graph headed "Relative Humidity. “The x-axis indicates the years "2019" through "2023." The y-axis displays the humidity percentage, which ranges from "4.8%" to "5.7%". The graph shows five points of information connected by a line. In "2019", the relative humidity was approximately "5%". In "2020", relative humidity increased significantly, reaching roughly "5.6%". In "2021," there was a significant reduction, putting it down around its "2019" level of roughly "5%". It indicates an increasing trend for "2022" and is projected or estimated for further rising into "2023".

Table IV compares the efficiency of three methods: SVR, RNN, and GRU-AE. The RMSE for GRU-AE 9.645 is higher than that of SVR 14.325 and RNN 12.253, suggesting greater accuracy. The MAE of GRU-AE 8.234 is also viable, displaying good predictive skills when contrasted with SVR 7.258 and RNN 7.688.

TABLE III. RELATIVE HUMIDITY OF ENVIRONMENT

Year	Relative Humidity (%)
2019	5.2
2020	5.6
2021	5.4
2022	5.1
2023	5.5

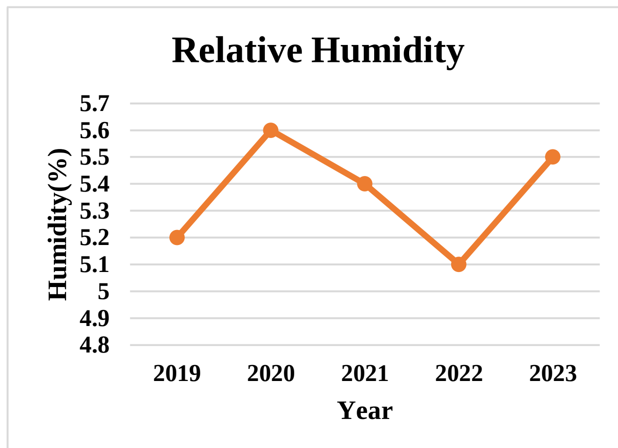

Fig. 5. Annual relative humidity.

B. Comparison of Proposed Method with Various Method

Fig. 6 compares the errors of three machine learning algorithms (GRU-AE, RNN, and SVR) utilising two error measures (MAE and RMSE). The x-axis indicates error levels, while the y-axis includes machine learning approaches. Each technique includes two bars, one for MAE and one for RMSE, giving the error levels. GRU-AE has an MAE of around 4 and an RMSE of a little over 12. RNN has an MAE and RMSE of about 8. SVR has an MAE of a little around 2 and an RMSE of 14. Table V depicts the various dataset comparison.

TABLE IV. PERFORMANCE METRICS [23]

Methods	RMSE	MAE
SVR [24]	14.325	7.258
RNN [25]	12.253	7.688
Proposed GRU-AE	9.645	8.234

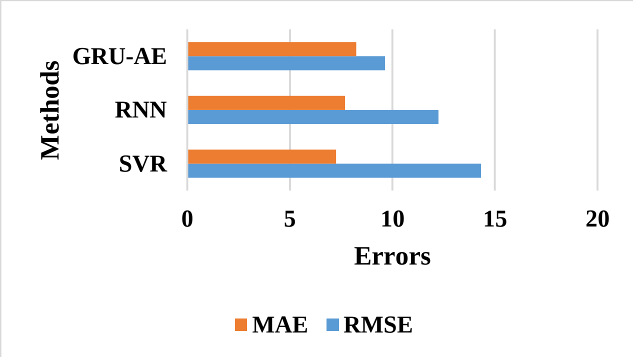

Fig. 6. Performance evaluation.

TABLE V. DATASET COMPARISON

Dataset	RMSE	MAE
Air Quality [26]	16.326	8.251
Global CO2 [27]	13.273	7.368
Proposed Environmental Monitoring Analysis	9.645	8.234

VI. DISCUSSION

The full assessment of the integrated system, which combines AI via the optimized GRU-Auto encoder and IoT-connected Advanced Optical Systems, yields promising results in enhancing sustainable energy and environmental monitoring. The model's generalization performance, as measured against a different test dataset, proves its capacity to properly forecast environmental changes and optimize energy use. The successful verification of the model's capacity to capture complicated temporal trends emphasizes its flexibility to changing environmental circumstances. When compared to existing approaches SVR, RNN, the optimized GRU-Auto encoder shows significant gains in efficiency and accuracy, demonstrating its potential to revolutionize real-time analysis of information in sustainable energy and environmental management. The higher performance is obvious across multiple parameters, including reduced MSE, greater accuracy, and increased precision, confirming the usefulness of the suggested technique.

Besides quantitative indicators, the debate focuses on the research's larger implications. The combination of an optimized GRU-Auto encoder with Advanced Optical Systems improves predictive capabilities while also contributing to sustainability goals. The system's capacity to optimize energy use is consistent with the growing focus on resource conservation and environmentally friendly practices. The discussion focuses on the practical implications of these discoveries, namely the integrated system's possible real-world applications in smart cities, renewable energy management, and environmental conservation initiatives. The study emphasizes the need to use modern artificial intelligence in conjunction with Internet of Things (IoT) structures to address current difficulties in sustainable energy and environmental monitoring, setting the groundwork for more robust and adaptable systems in the future.

VII. CONCLUSION

The optimized GRU-Auto encoder in Advanced Optical Systems combines AI with IoT, representing a big step forward in sustainable energy and environmental monitoring. The results of this research show the system's capability for real-time monitoring, precise forecasts of environmental patterns, and efficient energy usage optimization. Comparative evaluations with existing approaches confirm the suggested approach's advantages, emphasizing its ability to transform the monitoring system environment. The successful evaluation of the GRU-Auto encoder's flexibility in dynamic situations reinforces its use in dealing with the intricacies of environmental data. This study not only advances the frontier of technology but also highlights the practical consequences for sustainable practices, emphasizing the significance of cutting-edge AI approaches in ushering in the next phase of smart and resource-effective monitoring systems.

For future research, the investigation might be expanded to improve the model's interpretability, allowing stakeholders to obtain a better understanding of the elements driving predictions. Scalability issues and the incorporation of real-world restrictions might also be addressed to make the system more deployable in a variety of settings. Further study could concentrate on including more environmental factors and increasing the dataset to improve the model's resilience across different circumstances. Furthermore, the integration of sophisticated detection processes and the examination of federated learning methods might provide ways for future studies, guaranteeing the system's ability to adapt to new obstacles while contributing to the in-progress development of sustainable energy and environmental monitoring procedures.

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