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Hybrid Intelligence: Combining ML and Optimization for Carbon Reduction: A Review

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ABSTRACT:

Carbon dioxide (CO₂) emissions are a leading driver of climate change, contributing to global warming, ecosystem disruption, and negative health outcomes. Accurate forecasting of these emissions has become vital for designing mitigation strategies and guiding sustainable development. Conventional statistical models, while previously useful, often struggle with the nonlinear and rapidly changing nature of emission data. Advances in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), have shown significant potential by uncovering complex patterns and improving predictive reliability.

This paper examines recent developments in CO₂ emission forecasting, including gradient boosting, long short-term memory (LSTM) networks, transformer-based approaches, and hybrid frameworks that integrate optimization techniques. It also highlights the importance of explainable AI (XAI), which enhances transparency and provides interpretability for decision-makers. Findings indicate that hybrid AI-based models achieve superior performance by combining predictive accuracy with practical insights. Such approaches offer a scalable and transparent foundation for emission reduction efforts and support global sustainability objectives.

KEYWORDS: Carbon dioxide emissions, machine learning, deep learning, hybrid models, AI, forecasting, sustainability

1. INTRODUCTION

Carbon dioxide (CO₂) emissions are widely recognized as one of the main drivers of climate change, contributing to rising global temperatures, extreme weather events, and widespread environmental and public health challenges [1]–[3]. With industrialization, urbanization, and energy demand continuing to grow, global CO₂ levels are projected to rise further unless effective monitoring and mitigation strategies are implemented [4], [5]. Accurate forecasting of emissions is therefore essential for informing policies, guiding industrial operations, and supporting global sustainability initiatives [6], [7].

Conventional forecasting approaches, such as linear regression and time-series econometric models, often fail to account for the complexity and interdependencies inherent in emission data. Factors such as fluctuating energy consumption, industrial output, transport activity, and meteorological conditions interact in nonlinear and dynamic ways, making traditional models insufficient for high-precision forecasting.

Traditional statistical and econometric approaches have historically been used to predict CO₂ emissions [8], [9]. While these methods provide valuable baseline insights, they often struggle to capture the nonlinear, high-dimensional, and dynamic nature of emission drivers, which include energy consumption patterns, industrial activity, transportation, weather conditions, and policy interventions [2], [10]. As a result, their predictive accuracy can be limited, particularly over long-term horizons or in rapidly changing environments [11].

Recent advancements in artificial intelligence (AI) offer promising alternatives. Machine learning (ML) algorithms, such as gradient boosting and support vector machines, and deep learning (DL) models, including long short-term memory (LSTM) networks and transformer-based architectures, have demonstrated the ability to identify hidden patterns and temporal trends within large and complex datasets [4], [12], [13].

Artificial intelligence (AI) provides a promising alternative, offering advanced methods capable of learning intricate patterns from large and heterogeneous datasets. Machine learning (ML) algorithms, including ensemble techniques, and deep learning (DL) architectures like LSTM and Transformers, have demonstrated strong potential in capturing both temporal and spatial emission patterns. When combined with optimization strategies, these models can not only predict future emission trends but also suggest actionable mitigation measures. Incorporating explainable AI (XAI) further ensures that predictions are interpretable, allowing policymakers and stakeholders to understand the key drivers of emissions and make evidence-based decisions.

Additionally, the integration of optimization techniques allows predictive models to be directly linked to decision-making, enabling industries and policymakers to implement targeted carbon reduction strategies [14], [15]. Explainable AI (XAI) further enhances these frameworks by providing transparency and interpretability, which is critical for building stakeholder trust [1], [16].

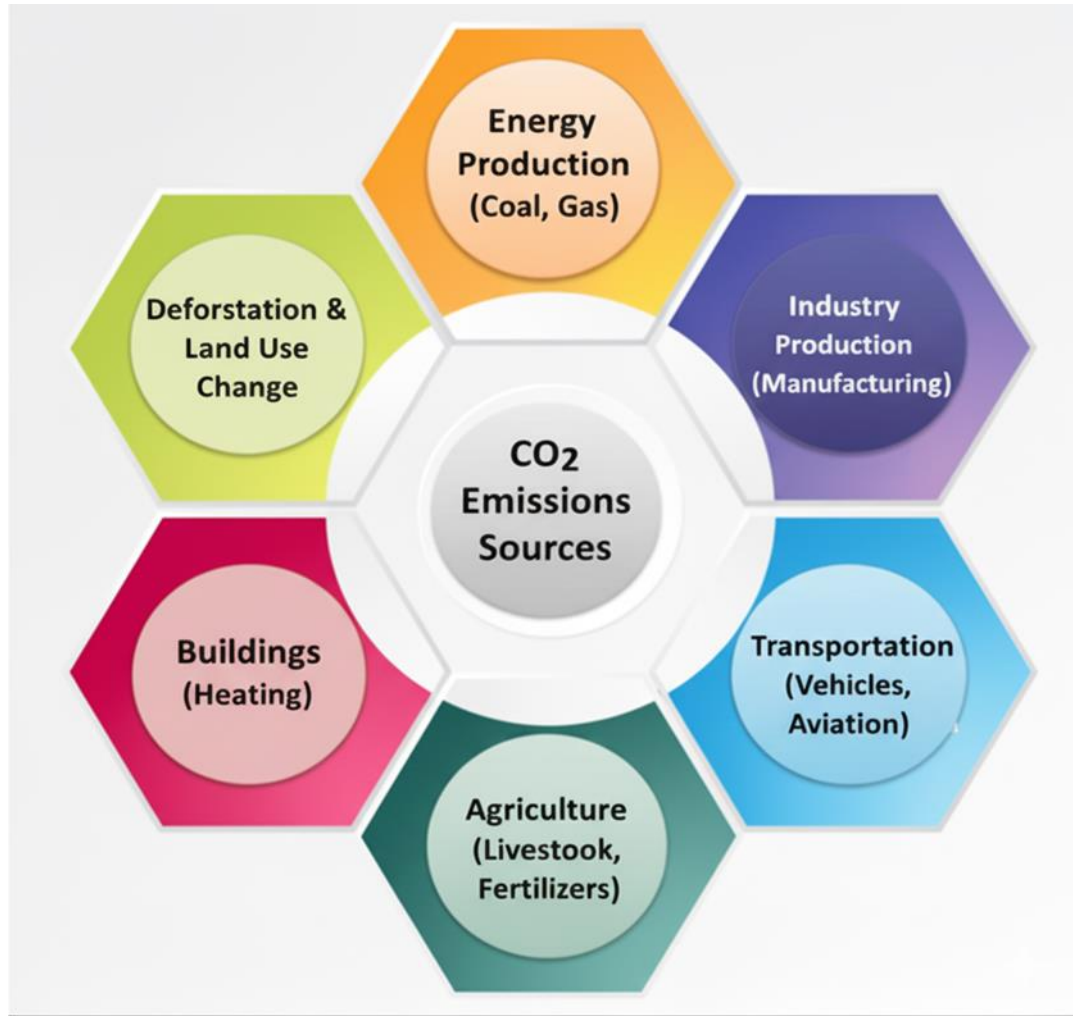


Fig. 1. Various carbon emission sources

Hybrid intelligent systems that combine ML, DL, optimization, and XAI have been increasingly applied to sector-specific and national-level CO₂ forecasting, achieving higher accuracy, robustness, and practical usability compared to conventional methods [5], [7], [12]. These approaches are capable of supporting real-time emission management, evaluating policy interventions, and assisting in the transition toward low-carbon operations.

This paper provides a comprehensive review of the latest AI-driven CO₂ emission prediction techniques, highlighting the advantages, limitations, and emerging trends in hybrid forecasting models. It emphasizes the potential of these systems to transform emission monitoring and mitigation efforts, bridging the gap between predictive analytics and actionable sustainability strategies.

2. Literature Review

The growing urgency to monitor and reduce carbon dioxide (CO₂) emissions has led to significant research efforts exploring artificial intelligence (AI) methods for accurate forecasting. Recent studies have shifted toward machine learning (ML) and deep learning (DL) approaches, which offer enhanced capability to model dynamic and high-dimensional interactions.

Deep learning model-based prediction of vehicle CO₂ emissions with eXplainable AI integration for sustainable environment: Alam et al., 2025

Alam et al. proposed a deep learning framework to forecast vehicle CO₂ emissions, integrating explainable AI (XAI) to provide interpretability of model outputs [1]. The methodology involved feeding historical vehicle and environmental data into a multilayer neural network while using XAI techniques to identify feature importance. The study demonstrated high predictive accuracy and offered insights into factors affecting emissions, aiding targeted interventions. However, the model was primarily validated on vehicle datasets, leaving its applicability to other sectors open for future exploration.

An examination of daily CO₂ emissions prediction through a comparative analysis of machine learning, deep learning, and statistical models: Ajala et al., 2025

Ajala et al. compared statistical models, classical machine learning, and deep learning techniques for daily CO₂ forecasting [2]. They employed datasets encompassing energy consumption and industrial activity, evaluating performance based on error metrics. The results showed that ML and DL approaches significantly outperformed statistical models in capturing nonlinear trends and temporal patterns. A limitation noted was that extremely high-frequency variations were not fully captured, suggesting room for incorporating more granular datasets.

Machine Learning in Carbon Capture, Utilization, Storage, and Transportation: A Review of Applications in Greenhouse Gas Emissions Reduction: Du et al., 2025

Du et al. provided a comprehensive overview of machine learning applications across the carbon capture, utilization, and storage (CCUS) process [16]. Their review highlighted how ML techniques are being used to optimize different stages, including absorbent selection in CO₂ capture, site characterization and leakage prediction in storage, and catalyst optimization for CO₂ utilization. The study emphasized that ML-driven methods can enhance operational efficiency and reduce costs in emission mitigation technologies. However, the authors noted that challenges persist in terms of data availability, model generalizability, and the interpretability required for large-scale industrial deployment.

Predicting carbon dioxide emissions using deep learning and Ninja Metaheuristic Optimization: Liebert & Ruple, 2025

Liebert and Ruple integrated deep learning with the Ninja Metaheuristic Optimization to predict emissions and simultaneously propose reduction strategies [3]. The deep neural network learned emission patterns while the optimization algorithm suggested parameter adjustments to minimize carbon output. This hybrid methodology improved forecast precision and decision-making capabilities, though its complexity may limit real-time deployment in resource-constrained environments.

Prediction of CO₂ emissions using machine learning — Bussaban et al., 2024

Bussaban et al. applied various machine learning algorithms for emission prediction [4]. They focused on the significance of feature selection and data preprocessing, demonstrating that well-tuned ML models can achieve higher accuracy, especially in regional or sector-specific datasets. The study highlighted the adaptability of ML for localized emission forecasting.

A Review of Machine Learning Used in Carbon Emission Prediction: Lu, 2024

Lu conducted an extensive review of more than 150 studies employing machine learning models for carbon emission prediction [18]. The analysis compared models such as Support Vector Machines, Random Forests, Gradient Boosting, and Deep Neural Networks, noting that ML consistently outperformed traditional statistical methods in both accuracy and adaptability. The review also identified key barriers such as inconsistent datasets, lack of transparency in complex models, and limited cross-domain applicability. The study concluded that future advancements should focus on improving data quality, hybrid model design, and interpretability to ensure practical adoption of AI-based forecasting systems.

Forecasting National CO₂ Emissions Worldwide: Costantini et al., 2024

Costantini and colleagues developed a large-scale forecasting framework to predict national CO₂ emissions across 117 countries up to the year 2035 [19]. They combined multivariate regression models and Random Forest algorithms using socio-economic and energy-related indicators. The model demonstrated that while developed economies are projected to experience gradual emission reductions, developing nations may continue to see emission growth due to industrial expansion. This study underscored the importance of integrating both environmental and economic indicators for more reliable and policy-relevant forecasts. Limitations included uneven data quality across countries and the need for continuous model retraining as global energy systems evolve.

Predicting CO₂ Emissions with Advanced Deep Learning Models: Feng et al., 2024

Feng et al. utilized LSTM and attention-based architectures to model temporal CO₂ emission trends [5]. The approach effectively captured complex nonlinear relationships in high-dimensional datasets and outperformed traditional statistical methods. Limitations included the requirement for extensive computational resources and large training datasets for optimal performance.

Forecasting energy-related carbon dioxide emission using artificial neural networks: Moayedi et al., 2024

Moayedi et al. focused on energy sector emissions using artificial neural networks [6]. The model incorporated variables like energy consumption, production indices, and industrial activity to predict CO₂ emissions. Their findings confirmed that ANNs are capable of modelling nonlinear interactions effectively, though the study noted potential overfitting risks if the network architecture is not properly tuned.

A Hybrid Ensemble ML Approach for Carbon Emission Forecasting: Li et al., 2023

Li et al. developed an ensemble ML framework combining multiple models, including Gradient Boosting and Random Forest, to improve predictive stability and accuracy [7]. The study highlighted that ensemble methods reduce variance and improve robustness across diverse datasets, making them suitable for complex emission forecasting tasks. However, ensemble models are computationally heavier and may require careful calibration to avoid overfitting.

Spatial-temporal prediction of CO₂ emissions based on deep learning: Hu et al., 2023

Hu et al. introduced a graph-based deep learning model to incorporate spatial and temporal dependencies simultaneously [8]. The model enabled precise, region-specific forecasts and highlighted the importance of considering both geographic and temporal factors in emission prediction. Limitations included dependency on high-quality spatial data and computationally intensive training procedures.

Forecasting the CO₂ Emissions at the Global Level: A Multilayer Artificial Neural Network Modelling: Jena et al., 2022

Jena et al. applied multilayer ANNs for global CO₂ forecasting, using aggregated international datasets covering energy consumption, population, and industrial metrics [9]. The study demonstrated the scalability of neural networks and their ability to capture global emission patterns. However, challenges remain in integrating real-time data and addressing missing or inconsistent datasets.

Predicting CO₂ Emission Footprint Using AI through Machine Learning: Meng & Noman, 2022

Meng and Noman employed ML to estimate CO₂ emission footprints [10]. They implemented regression-based and tree-based models on industry and energy datasets to produce actionable insights. Their work emphasized the role of predictive modelling in supporting targeted sustainability strategies and guiding policy interventions.

KEY INSIGHTS

Machine learning and deep learning approaches have consistently demonstrated higher accuracy and adaptability across sectors [1] – [10].

Deep learning architectures, particularly LSTM networks and attention-based models, effectively model temporal and high-dimensional emission data. Feng et al. [5] showed that attention mechanisms outperform traditional models, while Hu et al. [8] incorporated spatial-temporal dependencies for more precise regional predictions. Alam et al. [1] integrated explainable AI (XAI), enabling identification of key emission drivers such as energy use, industrial activity, and transportation.

Classical ML models, including Random Forest, Gradient Boosting, and hybrid ensembles, perform well for sector-specific or regional predictions. Li et al. [7] highlighted ensemble methods' ability to reduce variance, and Bussaban et al. [4] emphasized the role of feature selection and preprocessing in improving accuracy. Hybrid models combining deep learning with optimization algorithms further enhance prediction precision and provide actionable strategies for emission reduction [3].

Comparative insights reveal that deep learning generally surpasses traditional and classical ML models in handling complex patterns, while hybrid and ensemble approaches improve stability and interpretability. Explainable AI adds transparency, aiding informed decision-making. Challenges remain, including data quality, computational requirements, and scalability.

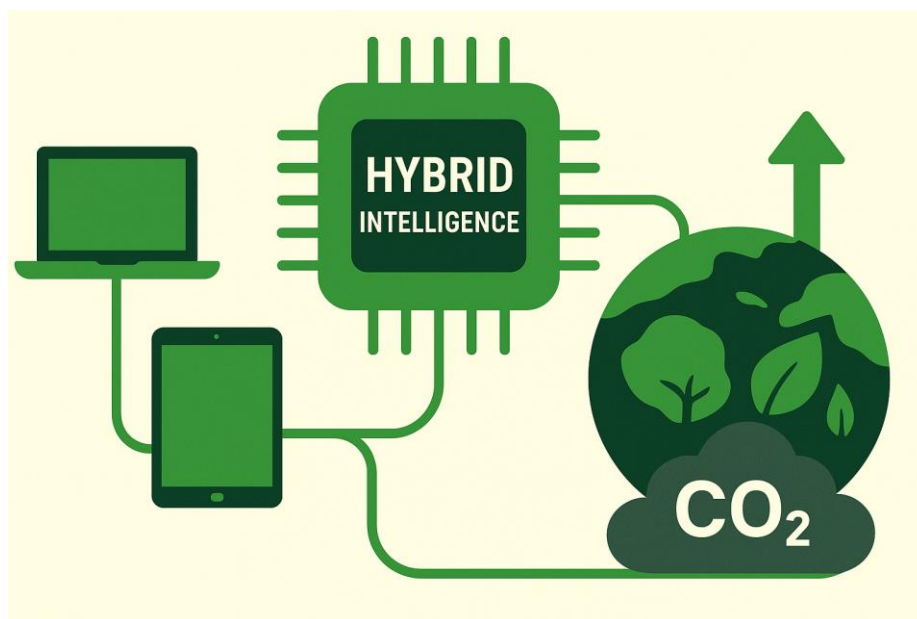


Fig. 2. Hybrid Computing and Environmental Sustainability

3.METHODOLOGY

The proposed framework is designed as a structured pipeline comprising multiple stages, including data acquisition, preprocessing, model training, testing, and prediction. Each phase is integral to optimizing the accuracy and efficiency of detection of lung cancer [10].

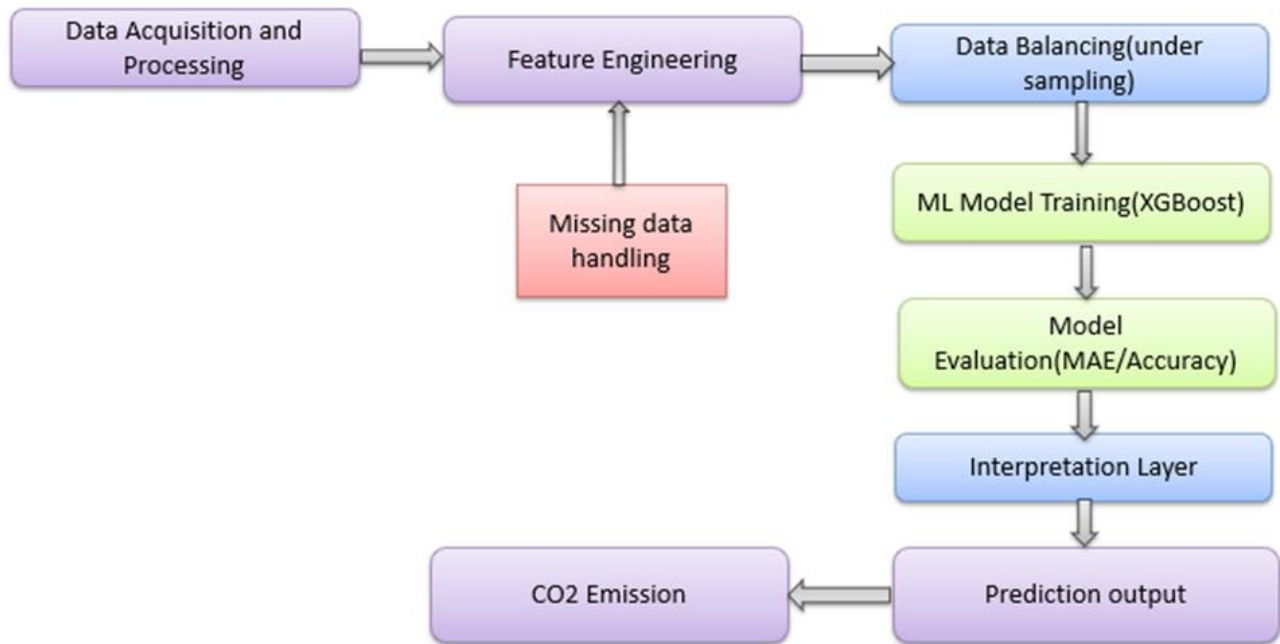


Fig. 3. Data flow diagram

The primary goal of this study is to accurately forecast CO₂ emissions using advanced artificial intelligence techniques while providing actionable insights for environmental decision-making. Based on the literature, hybrid deep learning models integrated with optimization techniques have demonstrated superior performance in capturing complex temporal, spatial, and nonlinear patterns in emission data. Building on these findings, the proposed methodology combines data preprocessing, model training, optimization, and evaluation in a structured framework.

3.1. Proposed Framework

Data Collection and Preprocessing:

The first step involves gathering comprehensive datasets, including historical CO₂ emission records, energy consumption statistics, industrial activity metrics, transportation data, and environmental parameters. Data is then cleaned to remove inconsistencies, missing values, and outliers. Feature selection is conducted using correlation analysis and domain knowledge to identify variables that significantly influence emissions. Normalization and scaling techniques are applied to ensure all features contribute proportionally during model training.

Model Selection and Architecture:

Deep learning models, particularly Long Short-Term Memory (LSTM) networks and attention-based architectures, are selected due to their ability to model temporal dependencies and capture long-term trends. LSTM layers are used to learn sequential patterns in emission data, while attention mechanisms enhance the network's focus on critical features influencing predictions. Additionally, a hybrid

framework integrates optimization algorithms, such as metaheuristic or ensemble methods, to fine-tune hyperparameters and enhance predictive performance.

Training and Validation:

The processed dataset is split into training, validation, and test sets. The model is trained iteratively using the training data while monitoring performance on the validation set to prevent overfitting. Techniques such as dropout regularization, early stopping, and learning rate scheduling are employed to improve generalizability. Hyperparameters, including the number of layers, learning rate, and batch size, are optimized using metaheuristic or grid search methods.

Prediction and Optimization:

Once trained, the model predicts future CO₂ emissions based on new input data. The integrated optimization component analyses these predictions to provide actionable recommendations for emission reduction strategies. This may include identifying the most influential emission sources or suggesting operational adjustments for industries and transportation systems.

3.2. Model Selection and Architecture

To enhance the predictive accuracy and interpretability of the proposed hybrid framework, the Extreme Gradient Boosting (XGBoost) algorithm is incorporated as a complementary model. XGBoost is a scalable ensemble learning technique that constructs multiple weak learners typically decision trees in a sequential manner. Each successive tree is designed to correct the prediction errors of its predecessors, thus reducing bias and improving model robustness.

Data Preprocessing:

Prior to model training, the dataset undergoes essential cleaning, encoding, and normalization to ensure uniformity across all variables. Missing values are handled appropriately, and the processed data is divided into training and validation subsets to enable reliable model evaluation.

Model Initialization:

The algorithm begins by setting key hyperparameters such as the number of trees, learning rate (η), and maximum tree depth. The initial predictions ($\hat{y}_i^{(0)}$) for all samples are initialized to zero or to the mean of the target variable.

Iterative Boosting Process:

At each boosting round t , XGBoost minimizes a regularized objective function that balances prediction accuracy and model complexity. The model calculates first-order gradients (g_i) and second-order gradients (h_i) of the loss function with respect to the predicted outputs, which represent the direction and curvature of the loss surface. A new regression tree $f_t(x)$ is then built to fit these gradients and maximize the information gain obtained from each split.

The optimal weight assigned to each leaf node is given by:

$$w_j^* = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda}$$

where λ is the regularization parameter that prevents overfitting by penalizing complex models. The model predictions are updated iteratively according to:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(x_i)$$

where $f_t(x_i)$ denotes the prediction from the t^{th} regression tree, and η is the learning rate controlling each tree's contribution. This process continues until convergence or until a predefined number of iterations K is completed. The final prediction is the sum of contributions from all trees:

$$\hat{y}_i = \sum_{t=1}^K \eta f_t(x_i)$$

Model Evaluation and Optimization:

Model performance is evaluated using standard regression metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). Hyperparameters—including learning rate, tree depth, and number of estimators—are fine-tuned through grid search or metaheuristic optimization to enhance model generalization and predictive stability.

Feature Interpretation:

One of the key strengths of XGBoost lies in its interpretability. The contribution of each feature to the final prediction can be expressed as:

$$\hat{y}_i = \phi_0 + \sum_{j=1}^d \phi_j(x_{ij})$$

where $\phi_j(x_{ij})$ denotes the contribution of the j^{th} feature to the prediction for instance i , and ϕ_0 is the model bias term. This interpretive framework allows identification of the most influential environmental or industrial factors driving CO₂ emissions, providing valuable insights for sustainable decision-making.

4. DISCUSSION AND ANALYSIS

The literature on CO₂ emission forecasting highlights a clear progression in methodologies, moving from traditional statistical approaches to advanced artificial intelligence techniques. Early statistical models, while useful for identifying general trends, often struggle to capture the complex, nonlinear, and temporal relationships inherent in emission data. This limitation has driven the adoption of machine learning and deep learning approaches, which offer greater flexibility and predictive power across diverse datasets [2,4,10,12].

Deep learning models, particularly LSTM networks and attention-based architectures, have shown strong capability in modelling temporal and high-dimensional patterns in CO₂ emissions. Attention mechanisms further enhance model performance by focusing on the most relevant features, improving

both accuracy and interpretability [5,8]. Graph-based deep learning models have also incorporated spatial dependencies, enabling precise, region-specific forecasts [8]. These approaches demonstrate that deep learning is well-suited for capturing complex emission dynamics, although they typically require substantial computational resources and large datasets for optimal performance [5,6,9].

Classical ML techniques, including Random Forest, Gradient Boosting, and XGBoost, have also been effective, particularly for sector-specific or regional forecasting [7,10,12]. Gradient boosting models, such as XGBoost, efficiently handle nonlinear interactions and provide interpretable feature importance metrics, making them a practical alternative to computationally intensive deep learning models [7,10]. Ensemble frameworks, which combine multiple models, further enhance prediction stability and reduce variance, ensuring more reliable performance across diverse datasets [7,12].

Hybrid approaches that integrate deep learning with optimization algorithms or ensemble strategies represent another promising avenue. These methods not only improve forecasting accuracy but also offer actionable insights for emission reduction, bridging the gap between prediction and practical application [3,7]. Moreover, the integration of explainable AI (XAI) techniques allows stakeholders to identify key emission drivers such as energy consumption, industrial activity, and transportation patterns supporting informed policy and operational decisions [1].

Despite these advances, challenges remain. Data quality, completeness, and granularity are critical for reliable forecasting [2,8,12]. Computational demands of deep learning and hybrid models can limit scalability and real-time applicability [5,6]. Additionally, sectoral and regional differences necessitate careful adaptation and tuning of models to maintain predictive performance [4,7].

Overall, the literature indicates that deep learning models excel at capturing complex temporal and spatial emission patterns, while classical machine learning models such as XGBoost provide an efficient, interpretable alternative for smaller or less computationally intensive datasets [7,10]. Hybrid and ensemble approaches offer a balanced solution, combining accuracy, robustness, and practical applicability. The incorporation of explainable AI enhances the value of these models by clarifying the factors driving CO₂ emissions, making AI-driven forecasting a powerful tool for both analysis and actionable sustainability strategies [1,3,7].

Nonetheless, the collective findings indicate that AI-driven approaches especially hybrid and explainable models represent the most promising solutions for accurate, interpretable, and actionable CO₂ emission forecasting.

Key Insights from Literature:

- Deep learning outperforms traditional statistical methods in modelling nonlinear and temporal emission patterns.
- Hybrid frameworks combining AI with optimization improve precision and decision-making capabilities.
- Explainable AI enhances transparency, highlighting the key drivers of emissions for targeted mitigation.
- Data quality and accessibility are critical determinants of model reliability and generalizability.

5.CONCLUSION

The forecasting of CO₂ emissions has advanced significantly with the adoption of artificial intelligence techniques. While traditional statistical methods provided foundational insights, they are often inadequate for capturing the complex, nonlinear, and temporal patterns present in emission data. Machine learning, deep learning, and hybrid frameworks have demonstrated enhanced predictive capability, with architectures such as LSTM networks, attention mechanisms, and ensemble models effectively handling both regional and global emission trends.

The incorporation of hybrid strategies and explainable AI has further strengthened these models, enabling not only precise predictions but also the identification of the key factors influencing emissions. Such insights are invaluable for policymakers, industry stakeholders, and environmental planners in designing targeted mitigation strategies.

But, challenges remain, including data quality, model generalizability across different regions and sectors, and computational demands. Addressing these challenges will be critical for the development of more efficient, scalable, and interpretable forecasting models.

In conclusion, AI-driven forecasting frameworks offer a reliable, interpretable, and scalable approach to CO₂ emission prediction. By combining predictive accuracy with actionable insights, these models can support informed decision-making, shape effective environmental policies, and contribute meaningfully to global efforts to reduce the carbon footprint.

6. FUTURE PROSPECTIVES

In last, there is a pressing need to develop more sophisticated and efficient models to tackle environmental pollution effectively. Technological advancements offer significant opportunities for improving pollution monitoring, control, and remediation strategies. In particular, hybrid intelligence approaches integrating machine learning, deep learning, and optimization methods hold great promise for addressing complex environmental challenges. These approaches can enhance prediction accuracy, identify key contributors to pollution, and support informed decision-making. Continued research in this area is crucial to create innovative, scalable, and practical solutions for sustainable environmental management.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests.

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