Neural Networks for Predicting Market Trends in Sustainable Industries: A Review

Frédéric Mirindi[1*] and Derrick Mirindi[2]

[1]Department of Economics, University of Manitoba, Winnipeg, Canada
[2]School of Architecture and Planning, Morgan State University, Baltimore, MD, USA

*Corresponding author e-mail id: mirindif@myumanitoba.ca
Frederic.mirindi@boothuc.ca

Abstract. Neural networks (NN) are increasingly acknowledged as effective tools for forecasting market trends in sustainable industries, providing the ability to improve decision-making in complex, dynamic environments. This paper provides a review of current research employing NN for forecasting trends in key sustainable fields, specifically energy, finance, and construction. It explores diverse NN architectures, their mathematical underpinnings, and practical applications such as energy demand forecasting, sustainable finance approaches, and construction workflow optimization. Consideration is given to the particular advantages NN offer in handling non-linear patterns and adapting to variable market dynamics. While significant obstacles related to data accessibility and model interpretability persists, the outlook for NNin sustainable industries is encouraging. Advancements in explainable AI (XAI), Green AI initiatives, and real-time adaptive systems bolster this positive outlook. In an era where sustainability is paramount, NN are poised to contribute substantially to innovation and the global transition toward a more sustainable future.

Keywords: Neural Networks, Sustainable Industries, Trend Forecasting

1 Introduction

The growing focus on environmental stewardship and resource efficiency within the global economy has spurred considerable interest in applying artificial intelligence (AI) to sustainable industries (Rana and Pathak, 2021).NN, a key component of the AI toolkit, are now widely employed as instruments for crucial tasks such as market trend forecasting, resource optimization, and enhanced decision-making across vital sustainable sectors including energy, finance, and construction. Sectors such as energy, finance, and construction face distinct hurdles, including demand volatility, evolving regulations, and the need for resource allocation optimization. Navigating these challenges necessitates reliable market forecasting, which underscores the critical role of sustainability efforts (LeCun, Bengio, and Hinton, 2015; Rana and Pathak, 2021; Mirindi, Khang, and Mirindi, 2025).

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The existing body of research demonstrates considerable NN adoption across diverse domains. In finance, for example, deep learning models particularly Long Short-Term Memory (LSTM) networks are utilized to predict stock market behavior through analysis of time-series data and market sentiment (Fischer and Krauss, 2018; Huo, Lou, Han, 2024). Likewise, the energy domain leverages AI models for electricity demand forecasting and smart grid optimization, thereby facilitating greater integration of renewable resources (Wen, Zhou, and Konstantin, 2023). The construction industry also sees benefits, using NN to advance sustainable building by improving energy efficiency modeling and predicting infrastructure maintenance needs (Wang et al., 2019; Mangalathu et al., 2020; Ahmed et al., 2022).

Progress in predictive modeling using NN has been substantial; however, critical gaps within the existing body of research require attention. Much of the current research focuses on applying NN within individual sectors, but comprehensive evaluations of their aggregate influence across the wider sustainable industry context are less common. Further research is particularly needed concerning the integration of specific sustainability indicators, for example, carbon footprint metrics, Environmental, Social, and Governance (ESG) criteria, and compliance factors, directly into the architecture or input features of NN models. Consequently, this study undertakes a thorough review of NN applications within sustainable industries, assessing their effectiveness, inherent challenges, and future possibilities.

The central research question guiding this work is: *How effectively can NN forecast market trends within sustainable industries, and what constraints arise from data availability, model interpretability, and adaptability requirements?* Correspondingly, this study proposes the following hypotheses:

- Neural networks markedly enhance trend prediction precision in sustainable industries relative to conventional forecasting models.
- Challenges related to data quality and interpretability hinder the extensive adoption of neural networks in sustainability-oriented market forecasting.
- Investigating whether the incorporation of specialized sustainability metrics can improve the predictive efficacy of neural network models remains a key research direction.

The significance of this research extends to multiple stakeholder communities. From an academic perspective, it adds to the understanding of AI applications in sustainability by integrating findings across different sectors. Industry professionals gain insights regarding the practical implementation of NN, which can inform operational strategies and business planning. Additionally, the findings offer potentially valuable input for policymakers developing regulatory approaches and sustainability guidelines.

The discussion unfolds as follows: Section 2 examines how NNare utilized in the energy, finance, and construction sectors of the sustainable economy. Section 3 then transitions to analyzing the benefits these networks offer for trend forecasting, highlighting their aptitude for modeling intricate relationships and adjusting to market volatility. In Section 4, the paper addresses the associated difficulties and constraints, concentrating on data-related issues and the challenge of interpretability. Concluding the review, Section 5 maps out potential pathways for future investigation.

2 Applications of Neural Networks

NN are increasingly vital in sustainable industries due to their ability to analyze large, complex datasets and identify patterns crucial for decision-making (Ahmed et al., 2022a). Their ability to model non-linear relationships facilitates adaptation to emerging sustainability challenges, improving efficiency across sectors such as energy, finance, and construction (e.g., (LeCun et al., 1998); (Bengio and Courville, 2013)).

A basic feedforward neural network layer transforms an input h_{l-1} (or the initial input X) to an output h_l using weights W_l, biases b_l, and a non-linear activation function σ (Bengio and Courville ,2013):

$$h_l = \sigma(W_l h_{l-1} + b_l) \ (1)$$

While various architectures exist (RNNs, LSTMs (Hochreiter & Schmidhuber, 1997), CNNs (LeCun et al., 1998), their application is tailored to specific industry needs.

2.1 NN in the Energy Sector

NN addresses challenges such as demand volatility and the integration of renewable energy (Wen, Zhou, and Konstantin, 2023).

Forecasting Renewable Energy

Predicting renewable energy (solar, wind) is essential for grid stability but challenging due to intermittency (Mellit, 2008). Traditional models such as ARIMA often fail with non-linear energy data (Janacek, 2010). NN, especially LSTM networks, excel by modeling long-range dependencies in sequential data (Rana and Pathak, 2021).

LSTMs use specialized gates to control information flow (Gers, Schmidhuber, and Cummins, 2000). Key components include:

- Forget gate (f_t): Decides what information to discard from the cell state.

$$f_t = \sigma\left(W_f h_{t-1} + U_f X_t + b_f\right)$$

- Input gate (i_t): Controls updates to the cell state .

$$i_t = \sigma(W_i h_{t-1} + U_i X_t + b_i)$$

- Output gate (o_t): Determines the next hidden state based on the filtered cell state.

$$o_t = \sigma(W_o h_{t-1} + U_o X_t + b_o)$$

- Cell State (C_t): Maintains long-term memory, updated based on forget and input gates.

$$C_t = f_t \circ C_{t-1} + i_t \circ \tanh(W_c h_{t-1} + U_c X_t + b_c)$$

(where ∘ denotes element-wise multiplication)

These mechanisms allow LSTMs to capture complex temporal dynamics by integrating historical usage, meteorological data, and grid conditions (San, Singh, and Prakash N., 2023).

- Applications: Solar energy prediction (Voyant et al., 2017), wind energy forecasting (Alshehri, Alzahrani, and Khalid, 2019), smart grid optimization (Manoharan, 2025).

Decision Trees for Energy Prediction

Decision Trees (DTs) offer an interpretable, rule-based alternative (Quinlan, 1987a). They partition data based on feature values, often aiming to reduce impurity. Common criteria include:

- Entropy (for ID3): Measures disorder in a set S.

$$H(S) = -\sum_{i=1}^{c} p_i \log_2 p_i$$

- Gini Impurity (for CART): Measures the probability of incorrect classification (related to CART algorithm concept).

$$Gini(S) = 1 - \sum_{i=1}^{c} p_i^2$$

For regression (predicting continuous demand), Mean Squared Error (MSE) is often minimized (Freedman, 2009):

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y})^2$$

Forecasting Solar Energy Output Example

NN can be combined with statistical techniques for improved forecasting and uncertainty quantification.

Figure 1 illustrates a simulated daily solar output forecast, showing fluctuations, a smoothed trend, and uncertainty. This visualization was created by generating synthetic daily time-series data with added seasonality (sine wave) and random noise, subsequently plotted alongside simulated uncertainty bounds and a LOESS (Locally Estimated Scatterplot Smoothing) trend line using R's ggplot2 package.

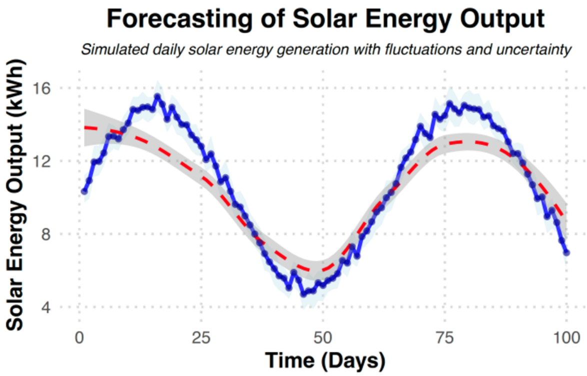

Fig. 1. Forecasting of Solar Energy Output

2.2 Neural Networks in Financial Markets

Financial markets encompass volatile, high-frequency data in which neural networks surpass conventional models such as ARIMA or GARCH (Bollerslev, 1995; Fischer and Krauss, 2018). RNNs, LSTMs, and GRUs (Cho et al., 2014) effectively model time-series data (Fischer and Krauss 2018); (Huo and Lou, 2024).

Financial Time-Series Prediction

Advanced approaches model specific financial behaviors:

- Neural Stochastic Differential Equations (SDEs): Model asset prices (S_t) considering drift (μ) and volatility (σ) driven by a Wiener process (dW_t). NN approximate μ and σ.

$$dS_t = \mu(S_t, t)dt + \sigma(S_t, t)dW_t$$

- Neural Jump-Diffusion Models: Extend SDEs to include sudden market jumps (J_t) governed by a Poisson process (dN_t) (related to Merton model concept).

$$dS_t = \mu S_t dt + \sigma S_t dW_t + J_t dN_t$$

  NNcan model the jump component J_t.

- Applications: Stock prediction (Fischer and Krauss, 2018; Huo and Lou, 2024), volatility modeling (related to Bollerslev (1995), Forex prediction, options pricing, credit risk assessment.

Decision Trees for Financial Market Prediction

DTs offer effective and interpretable models for applications such as credit scoring and risk evaluation. Regression trees often use variance reduction or error metrics,for example, MAE or MSE for splitting. Ensemble methods are common:

- Random Forests (RF): Average predictions from multiple trees (f_m) trained on data subsets (related to Breiman (2001) RF concept).

$$\hat{y} = \frac{1}{M}\sum_{m=1}^{M} f_m(X)$$

- Gradient Boosting (e.g., XGBoost): Sequentially adds weak learners (h_t) to correct prior errors (related to Breiman, 2001) boosting concept).

$$\hat{y}^{(t)} = \hat{y}^{(t-1)} + \eta \cdot h_t(X)$$

2.3 Neural Networks in the Construction Sector

Construction involves complexity and uncertainty in forecasting timelines, costs, and risks. NN, particularly LSTMs, manage sequential project data effectively (Ahmed et al., 2022b; Wang et al., 2019).

Forecasting Construction Variables

LSTMs model construction variables by learning from historical data and exogenous factors. Their memory mechanism (similar to equations in 2.1.1) captures long-term project dynamics. Advanced models include:

- Neural Jump-Diffusion Models (NJDMs): Adapt jump-diffusion concepts (see 2.2.1) to forecast high-impact construction disruptions.
- Hybrid Transformer-LSTM Models: Combine LSTMs (short-term dependencies) with Transformers (long-range dependencies via self-attention).
- Applications: Project completion prediction, cost forecasting, material demand prediction (Ahmed et al., 2022b), weather impact assessment.

Decision Trees & Other Methods in Construction Forecasting

DTs offer interpretable, rule-based forecasting for construction (related to Quinlan (1987b)). They split data based on features,particularly project size, workforce, material costs, etc., often minimizing variance or MSE. Ensembles (RF, XGBoost) and other methods (SVMs, Bayesian Networks, KNN) are also used (Mangalathu et al., 2020).

Forecasting Concrete Strength Example

Predicting concrete strength is vital for quality control. NNcan model the non-linear strength development over curing time. Figure 2 shows a forecast of concrete strength development, illustrating the typical gain curve and prediction uncertainty. This visualization utilizes synthetic data generated via a logarithmic function (to mimic strength gain over time) with added random noise, plotted with simulated uncertainty bounds and visualized using a LOESS (Locally Estimated Scatterplot Smoothing) trend line in R's ggplot2 package.

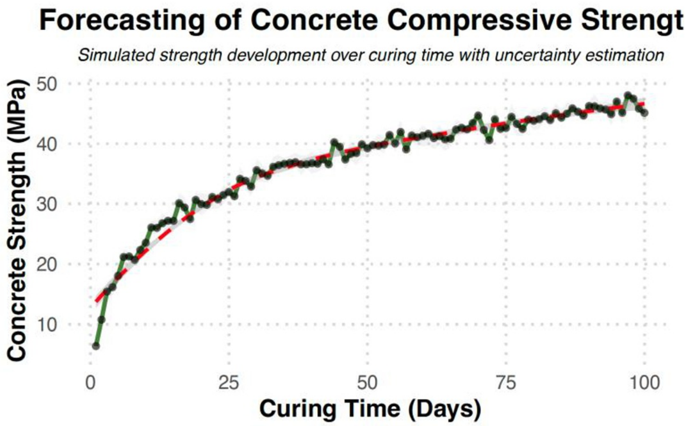

Fig. 2. Forecasting of Concrete Compressive Strength

3 Advantages of Neural Networks in Trend Prediction

NN offer significant advantages for trend prediction in sustainable fields including construction, energy, and finance, surpassing traditional statistical models in accuracy, adaptability, and robustness. Unlike methods assuming predefined data structures, NN autonomously learn complex patterns and dynamic relationships, making them effective for intricate forecasting challenges (LeCun, Bengio, and Hinton, 2015). The integration of advanced architectures,particularly Graph Neural Networks (GNNs), Transformers, and Neural Stochastic Differential Equations (Neural SDEs) further enhances predictive analytics, making models more context-aware and resilient.Figure 3 provides a visual summary of these key advantages discussed in this section.

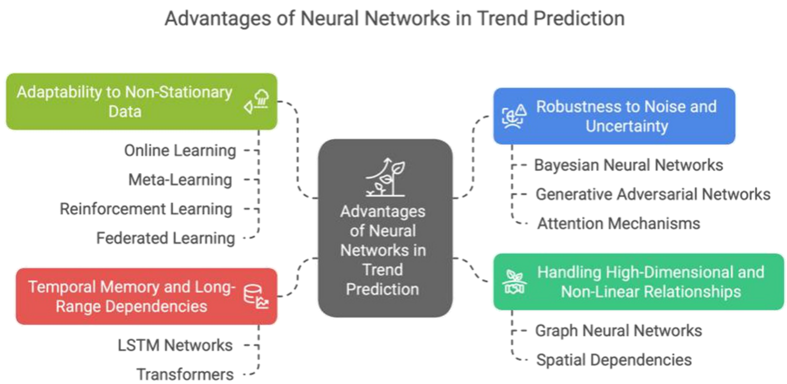

Fig. 3. Overview of Advantages of Neural Networks in Trend Prediction

3.1 Handling High-Dimensional and Non-Linear Relationships

Sustainability problems often involve non-linear interactions (e.g., climate effects on energy, complex construction cost factors) that conventional models may not adequately capture. NN excel at extracting multi-level features, revealing underlying dependencies among diverse variables. GNNs, for instance, effectively model spatial or relational dependencies, applicable to tasks including supply chain optimization, energy grid stability analysis, or predicting infrastructure risks.

3.2 Temporal Memory and Long-Range Dependencies

Forecasting in sustainable industries requires capturing both long-term trends and short-term variations. While traditional time-series models, especially ARIMA can struggle with long-range memory (Janacek, 2010), advanced NN such as LSTM networks (Hochreiter and Schmidhuber, 1997) are specifically designed to retain information over extended sequences. Architectures in particular Transformers (using self-attention, related to Vaswani et al., 2017 concept) dynamically adapt to varying temporal patterns (e.g., seasonality in renewable energy). Furthermore, methods especially Neural Controlled Differential Equations (NCDEs) model continuous-time processes for precise forecasting, while Physics-Informed Neural Networks (PINNs) incorporate domain knowledge (physical laws) to ensure realistic predictions in engineering and environmental applications.

3.3 Adaptability to Non-Stationary Data

Sustainable systems operate in dynamic environments influenced by policy changes, climate shifts, and technological evolution. NN offer adaptability through various learning paradigms:

- Online learning: enables models to modify parameters instantaneously as new data is received, essential for applications such as adaptive energy demand forecasting.
- Meta-Learning: improves model generalization, particularly in scenarios with limited data.
- Reinforcement Learning RL: enables automated, optimized decision-making under uncertainty, relevant for managing energy distribution or deploying autonomous systems in construction.
- Federated Learning (FL): facilitates collaborative model training across decentralized datasets without compromising privacy, valuable for multi-regional grid optimization or climate modeling.

3.4 Robustness to Noise and Uncertainty

Predictive models should handle imperfect data, including noise, missing values, and unexpected events. NN can incorporate mechanisms to improve reliability:

- Bayesian Neural Networks (BNNs): Introduce probabilistic methods to provide confidence estimates alongside predictions, useful for risk assessment. *
- Generative Adversarial Networks (GANs): Can generate synthetic data to augment limited datasets or simulate complex scenarios.
- Attention Mechanisms (e.g., in Transformers): Help models focus on relevant information while filtering out noise, improving signal detection in volatile financial markets or construction project monitoring.

These capabilities allow industries to better anticipate disruptions, manage risks, and make informed decisions.

3.5 Outlook for Trend Prediction

NN continue to advance forecasting capabilities in sustainable sectors. Hybrid approaches combining different AI techniques (e.g., NDEs, RL, Transformers) promise further improvements. Future applications may include more sophisticated AI-driven optimization in construction logistics, enhanced demand-response strategies in smart grids, and more adaptive forecasting models for green finance and ESG risk analysis. These innovations are key to accelerating the transition towards more sustainable and resilient practices across various industries.

4 Challenges and Limitations of Neural Networks in Trend Prediction

Despite significant advancements, applyingNN for trend prediction in sustainability-focused sectors,especially construction, energy, and finance, faces notable hurdles. Key limitations arise from data availability, model transparency, computational demands, and ethical factors. Figure 4 visually summarizes these primary challenges. Addressing these is crucial for fully realizing the potential of NN in critical decision-making processes.

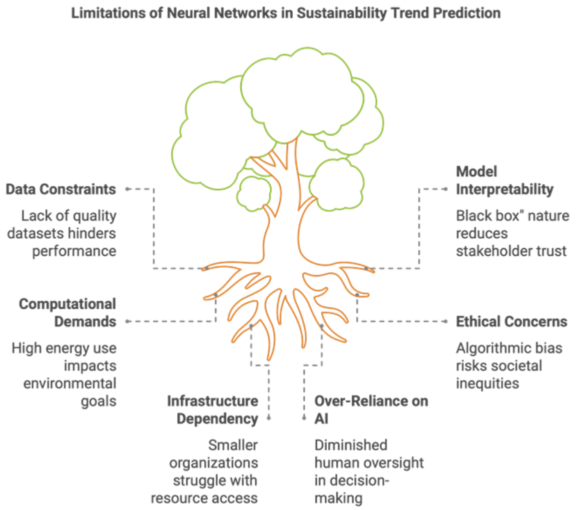

Fig. 4. Key Limitations of NN in Sustainability Trend Prediction

4.1. Data Constraints and Quality

Effective NN performance hinges on high-quality, comprehensive datasets, which are often lacking in sustainable domains. Common issues include:

- Data scarcity: limited historical data exists for newer initiatives (e.g., novel sustainable materials, adaptive grids).
- Data heterogeneity: integrating diverse, unstructured sources (sensors, images, reports) remains complex.
- Data bias: models trained on data from one region may not generalize well to others with different conditions or regulations. Solutions being explored involve synthetic data generation (e.g., using GANs), transfer learning, and multimodal data fusion techniques to improve model robustness and applicability.

4.2. Model Interpretability and Causality

The "black box" nature of many deep learning models poses a significant challenge, especially in high-stakes applications where trust and validation are paramount. Specific difficulties include:

- Opacity: stakeholders struggle to understand or validate the reasoning behind AI-driven recommendations.
- Lack of causal insight: NN excel at pattern recognition but often cannot explain the underlying causal relationships driving predictions (e.g., the root causes of construction cost overruns).

- Accountability: ensuring auditability and explainability is vital for regulatory compliance and legal accountability in areas such as carbon offsetting or safety assessments. Progress in Explainable AI (XAI), including methods such as SHAP and LIME, along with Causal AI and Neuro-Symbolic approaches, aims to increase transparency without sacrificing predictive power.

4.3 Computational Resources and Energy Sustainability

Training sophisticated NN demands substantial computational power and energy, raising concerns about the environmental footprint of AI itself, particularly in sustainability contexts. Key problems are:

- High energy use: large models (Transformers, GNNs) require significant energy for training, contributing to carbon emissions.
- Scalability: real-time, low-latency predictions needed in some applications can be challenging to scale efficiently.
- Infrastructure dependency: reliance on high-performance computing (HPC) can be a barrier for smaller organizations. The "Green AI" initiative promotes energy-efficient approaches, for instance, neuro-morphic computing, sparse network architectures, and federated learning to mitigate these issues.

4.4 Ethical and Social Implications

The deployment of AI in sustainability forecasting carries significant societal and ethical weight. Major concerns involve:

- Algorithmic bias: models may perpetuate or amplify existing societal inequities if trained on biased data (e.g., in urban infrastructure planning).
- Data privacy: sensitive information used in applications, for example, carbon footprint tracking or decentralized energy systems requires robust privacy protection.
- Over-Reliance: the potential diminishment of human expertise and oversight in critical decision-making requires careful consideration. Developing Fair AI principles, establishing strong ethical governance, and fostering human-AI collaboration are essential to mitigate these risks.

4.5 Addressing Challenges and Future Directions

Overcoming these limitations requires interdisciplinary collaboration. Future research frontiers could include developing hybrid models (e.g., combining PINNs, Bayesian methods, and graph-based AI) for more robust and interpretable solutions, creating self-learning systems that adapt continuously without full retraining, and establishing clear regulatory frameworks that align AI deployment with global sustainability standards, including ESG criteria. Successfully navigating these challenges will enable NN to play a truly transformative role in fostering sustainable infrastructure, resilient energy systems, and responsible financial markets.

5 Future Directions in Neural Network-Based Trend Prediction

As NN evolve, advancing their capabilities while addressing the challenges outlined previously is vital for their effective use in sustainability-focused industries. Future research should prioritize enhancing model explainability, improving energy efficiency, and enabling real-time adaptability to ensure AI-driven forecasting is reliable, transparent, and sustainable.

5.1. Advancing Explainable AI (XAI)

The increasing deployment of NN in critical decision-making roles necessitates greater transparency. Key directions in XAI include:

- Causal AI: moving beyond correlation to identify cause-and-effect relationships, providing deeper insights for risk assessment and planning.
- Neuro-Symbolic AI: integrating deep learning's pattern recognition with logic-based reasoning to enhance interpretability, particularly for rule-based systems in infrastructure or energy management.
- Attention-Based Transparency: using mechanisms within models such as Transformers to highlight influential input features, aiding real-time analysis in finance or predictive maintenance.

5.2 Developing Green AI and Sustainable NN

Addressing the significant energy consumption of deep learning is crucial. The "Green AI" initiative focuses on:

- Energy-Efficient Hardware: exploring neuromorphic computing, inspired by biological systems, for lower-power AI processing.
- Decentralized learning: utilizing federated and edge learning to train models collaboratively without high-energy centralized data processing.
- Model optimization: employing techniques including network sparsification and quantization to reduce computational load without significantly sacrificing accuracy.

5.3 Enhancing Real-Time Adaptation

Sustainable systems operate in dynamic environments, requiring AI models that can adapt quickly:

- Online/Incremental Learning: developing models that continuously learn from new data streams, essential for adaptive planning in construction, finance, and climate response.
- RL for Self-Optimization: using reinforcement learning to create systems that autonomously optimize decisions under uncertainty, applicable to energy grid management or robotics.

- Hybrid Physics-Informed AI: combining data-driven deep learning with domain-specific knowledge (e.g., physics, engineering principles) to improve accuracy and ensure realistic predictions.

5.4 Overarching Future Research Themes

Achieving a balance between predictive power, interpretability, and sustainability requires a holistic approach. Future efforts should concentrate on:

- Ethical AI governance: establishing clear frameworks for fairness, transparency, and bias mitigation in AI applications affecting society and the environment.
- Self-Adapting systems: creating AI models capable of autonomously adjusting to evolving regulations, market conditions, and environmental changes.
- Cross-Disciplinary collaboration: fostering partnerships between AI researchers, domain experts, policymakers, and industry leaders to ensure AI advancements align with practical needs and global sustainability goals.

NN can evolve into essential instruments, fostering innovation and facilitating informed, sustainable decision-making across various sectors by concentrating on these trajectories.

6 Conclusion

NN are proving to be powerful instruments for trend prediction and decision support within critical sustainable industries, including energy, finance, and construction. Their distinct advantage lies in modeling the complex, non-linear dynamics inherent in these fields, enabling deeper insights from diverse datasets using architectures such as LSTMs, Transformers, and GNNs. However, significant hurdles currently impede their broader adoption. Key challenges encompass data limitations (scarcity, quality, bias), the inherent lack of transparency in many deep learning models ("black box" problem), substantial computational and energy requirements raising sustainability concerns about AI itself, and pressing ethical considerations regarding fairness and privacy.

Overcoming these limitations necessitates continued innovation, particularly focused on Explainable AI (XAI) to build trust and accountability, Green AI initiatives to enhance energy efficiency, and adaptive learning systems capable of handling real-time, non-stationary data. Future progress will potentialy involve developing sophisticated hybrid models, creating self-learning systems that adapt to evolving conditions, explicitly integrating sustainability metrics such as ESG criteria into model design, establishing robust ethical governance, and fostering vital cross-disciplinary collaboration between AI experts, domain specialists, and policymakers. NN can fulfil their substantial potential by significantly enhancing the development of resilient infrastructure, sustainable energy systems, and environmentally aware financial markets worldwide through targeted research and responsible advancement.

Disclosure of Interests. The authors declare that there is no conflict of interests related to this research work

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