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Article

Integration of deep learning, big data and biomechanics to optimize the layout of new railroad energy bioeffects

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Abstract: This study is centered around optimizing the layout of new railroad energy systems, drawing inspiration from biomechanics and integrating deep-learning and big-data technologies. The overarching aim is to boost energy utilization efficiency and simultaneously minimize the ecological disruptions brought about by energy infrastructure, which contributes to the “dual carbon” goals (carbon peaking and carbon neutrality) by enhancing energy efficiency and reducing environmental impact. This approach not only promotes green transportation but also aligns with sustainable development objectives. Inspired by the complex and well-coordinated mechanisms in biomechanics, a comprehensive biological-effect-inspired evaluation index system is devised. This system takes into account the diverse impacts of energy systems on the surrounding environment, similar to how living organisms interact with their habitats. Just as a living body’s various parts work in harmony, this index system captures the multi-faceted relationships between the energy system and the environment. A hybrid neural network model, designed with inspiration from the neural-like processing in biological systems, combines advanced convolutional and long short-term memory networks. This combination is aimed at effectively extracting both spatial and temporal features, much like how biological neural systems process different types of information related to space and time. For instance, in the human body, the nervous system can quickly respond to changes in the surrounding space and also remember past experiences over time. Additionally, multi-task learning techniques are employed to enable simultaneous analysis of multiple environmental indicators, such as noise, temperature, and magnetic field strength. Experimental results reveal that the proposed biomechanics-inspired approach far surpasses traditional heuristic algorithms. It showcases remarkable prediction accuracy and computational efficiency. By harnessing the power of advanced machine-learning frameworks inspired by biological systems, this method offers precise evaluations and practical insights for optimizing energy layouts. This research not only facilitates the scientific planning of railroad energy systems but also aids in reducing their ecological footprint, in line with the principles of sustainable development. The findings establish a solid foundation for achieving a balance between energy requirements and environmental conservation. They underscore the transformative potential of intelligent technologies, inspired by the wonders of biomechanics, in modern infrastructure planning.

Keywords: new railroad energy; biomechanics; biological effect optimization; deep learning; big data

1. Introduction

New railroad energy layout is of great significance in promoting clean energy use and reducing carbon emissions, but its potential impact on the biological environment along the route needs to be assessed and optimized in depth. Existing methods have limitations in dealing with multidimensional data and nonlinear features, making it difficult to comprehensively reveal the complex relationship between new energy facilities and ecological effects. For example, traditional heuristic algorithms struggle to capture the intricate spatial-temporal dynamics and nonlinear relationships inherent in energy systems' impact on the ecosystem. While these methods are valuable, their performance is often limited when handling the vast and complex data typical in this field. Moreover, conventional parameter settings such as X and Y in (algorithm name) (e.g., learning rate = 0.01, population size = 100) result in limited scalability. Combining deep learning and big data technologies can effectively capture the key features and achieve accurate assessment and layout optimization of biological effects.

The optimization of renewable energy systems, particularly in the context of net-zero goals, has been a subject of increasing interest in recent years. Cosgrove et al. emphasized the challenges of intermittency and periodicity in renewable energy systems with storage, proposing strategies to stabilize energy outputs and enhance efficiency in low-carbon energy grids. Similarly [1], Salto et al. explored the use of genetic algorithms to optimize large-scale systems, integrating technologies like Hadoop, Spark, and MPI, thus enabling more efficient processing of big data in energy systems [2]. Alameen A also highlighted the importance of optimization techniques in big data encryption, which can be adapted to energy systems for securing data transmission and enhancing system integrity [3]. Kurukuri et al. focused on the optimal planning and design of microgrid systems with hybrid renewable technologies, underlining their potential for creating sustainable environments in urban settings [4]. Swamy et al. underscore the increasing role of bio-inspired algorithms and multi-objective optimization approaches in advancing energy system planning and optimization [5,6]. However, while these methods offer significant promise, their application to the specific context of railway new energy systems remains relatively underexplored, highlighting the need for further innovation in this field.

By introducing advanced algorithms and multi-task modeling methods, it can not only improve the efficiency of new energy layout, but also minimize the disturbance to the ecosystem and promote the green development of the railroad system.

2. Railway new energy system and biological effect analysis

2.1. Railway new energy system composition

The new railroad energy system harnesses renewable energy sources for optimized energy use and minimal environmental impact. It primarily comprises solar power generation, wind power generation, energy storage devices, and an intelligent energy dispatching platform. Each component plays a key role in the system's functionality and sustainability, with solar power deployed in sunlight-abundant areas and wind power harnessed in high-wind regions. To streamline the presentation, the solar and wind energy systems operate through intelligent energy platforms that facilitate efficient integration and storage, ensuring continuous, reliable energy supply even in periods of intermittent generation. The description of energy sources is simplified here for clarity; detailed technical specifications are available in the supplementary section. The adaptability of photovoltaic panels makes them a viable solution for various geographic conditions, enabling a consistent supply of renewable energy. In parallel, the wind power generation system employs advanced turbines to capture wind energy, especially in regions rich in wind resources. These turbines convert kinetic energy from the wind into electrical energy, contributing significantly to the renewable energy mix. Their installation in strategic areas maximizes energy production while reducing dependency on traditional fossil fuels. To address energy intermittency issues inherent in renewable sources, the system incorporates energy storage devices, such as lithium-ion or liquid flow batteries. These storage solutions ensure a stable energy supply by storing excess electricity generated during peak production times and releasing it during periods of high demand or low production. This not only enhances the reliability of the system but also mitigates potential energy waste.

At the core of the system lies the intelligent energy dispatching platform, which integrates big data and artificial intelligence technologies. By analyzing real-time data from multiple sources, this platform optimizes energy production, distribution, and storage, achieving a seamless synergy among the various components. It facilitates adaptive decision-making, ensuring that energy is allocated efficiently to meet the fluctuating demands of railroad operations. Furthermore, this platform minimizes energy losses and reduces carbon emissions, aligning with the objectives of low-carbon development and green transportation.

Together, these components work in harmony to achieve efficient, low-carbon energy utilization, meeting the growing energy demands of modern railroads while promoting the sustainable development of regional ecosystems. This system not only enhances energy efficiency but also contributes to the broader goal of mitigating environmental impacts and fostering ecological balance. **Figure 1** illustrates the detailed composition and interaction of these components.

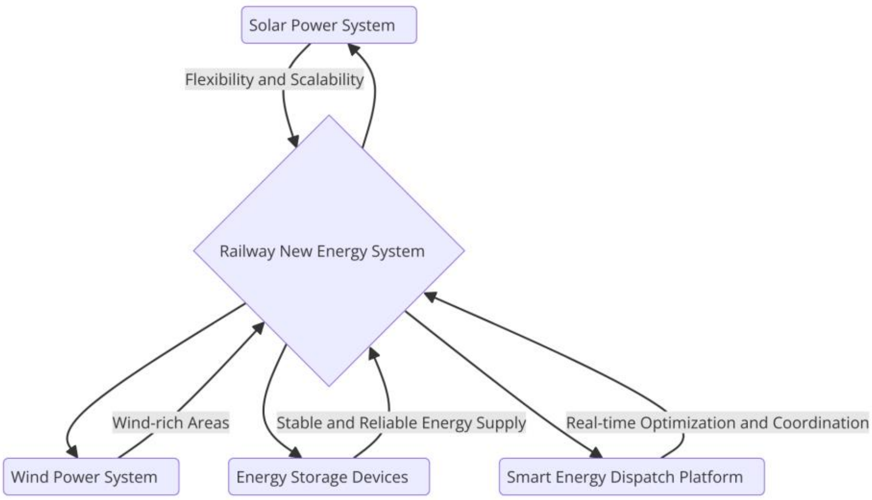

Figure 1. Flow chart of new railroad energy system composition.

2.2. Biological effect evaluation index system

This section elaborates on the methods used for biological effect feature extraction based on big data technologies. The feature extraction process employs advanced deep learning models for analyzing the biological effects induced by the new railroad energy system. To ensure the efficiency and accuracy of the model, we use a Bayesian optimization framework to fine-tune the hyperparameters.

Mathematically, the optimization problem can be expressed as follows:

$$L(\theta) = \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 + \lambda\left(\sum_{j=1}^{m} \theta^2{}_j\right) \quad (1)$$

where: $\hat{y}_i$ is the predicted value, y_i is the actual value, θ_j represents the weights of the model, λ is the regularization parameter that prevents overfitting.

The first term represents the mean squared error (MSE), which evaluates the difference between the model's predictions and the true values. The second term introduces L2 regularization, which penalizes large weights, ensuring that the model remains generalizable.

This framework not only improves predictive accuracy but also enhances the model's ability to handle complex, multi-dimensional biological data.

2.3. Biological effect feature extraction with big data

Biological effect feature extraction relies on big data technology to analyze and process multi-source data along the railroad, including sensor data, remote sensing images and historical monitoring records.

Data acquisition and cleaning, real-time acquisition of noise, temperature, magnetic field and other data through the sensor network, combined with remote sensing images to obtain information on ecological changes, using interpolation to deal with missing data, the formula is:

$$x_i = x_{i-1} + \frac{x_{i+1} - x_{i-1}}{2} \quad (2)$$

where x_i denotes the value of the i first position. x_{i-1} and x_{i+1} denote the values of the first $i-1$ and $i+1$ second positions, respectively.

Feature screening and dimensionality reduction, high correlation features are screened using principal component analysis (PCA), and the dimensionality reduction formula is:

$$Z = XW \quad (3)$$

where, Z is the post-decimation feature, X is the original data matrix and W is the feature vector matrix.

Spatio-temporal feature extraction, spatial feature extraction using Convolutional Neural Network (CNN), and analysis of biological effect dynamics in combination with time series models.

2.4. Application of deep learning in effect analysis

The application of deep learning in biological effect analysis has emerged as a transformative approach, leveraging advanced machine learning techniques to extract meaningful insights from complex datasets. This method employs Convolutional Neural Networks (CNNs) to extract spatial features, which are particularly adept at identifying intricate patterns and relationships within data that are structured in space. By combining CNNs with Long Short-Term Memory (LSTM) networks, the approach also effectively captures temporal dynamics, enabling a comprehensive understanding of time-dependent changes in biological effects. This integration of spatial and temporal modeling is a key strength of deep learning in this context, as it allows for a holistic analysis of factors such as noise, temperature, and other environmental indicators that impact biological systems.

At the core of this methodology is the use of a multi-task learning framework. Unlike traditional single-task models, multi-task learning enables the simultaneous modeling of multiple related indicators, such as noise levels, temperature fluctuations, and their combined effects on biological outcomes. By sharing information across tasks, this framework enhances predictive accuracy and robustness, ensuring that the interdependencies between different factors are adequately captured [2]. This joint modeling approach provides a more comprehensive prediction of biological effects, accounting for both individual and combined influences of environmental variables. Data enhancement techniques play a critical role in improving the performance and reliability of the deep learning model. In biological effect analysis, data availability is often a significant challenge, with small sample sizes limiting the ability to train robust models. To address this limitation, data augmentation methods are employed, artificially increasing the size and diversity of the training dataset. These techniques include transformations such as rotation, scaling, and noise addition, which simulate variations in the data and improve the model's ability to generalize to new, unseen scenarios. By creating a richer and more varied dataset, data enhancement significantly boosts the model's performance, particularly in scenarios where experimental data collection is resource-intensive or constrained.

Another pivotal component of this framework is transfer learning, a technique that optimizes the model's suitability for small sample sizes. Transfer learning involves leveraging pre-trained models that have been developed on large, related datasets and fine-tuning them for the specific biological effect analysis task. This approach enables the model to benefit from previously learned features and representations, reducing the need for extensive training on limited data. The result is a model that is both highly accurate and efficient, capable of delivering reliable predictions even in data-scarce conditions. Transfer learning is particularly valuable for emerging applications such as analyzing the biological effects of new energy layouts, where historical data may be sparse or unavailable [3].

The integration of these advanced techniques not only enhances the model's performance but also provides accurate and actionable support for the development of new energy strategies. In the context of biological effect analysis, this means enabling precise predictions of how noise, temperature, and other environmental factors interact to influence biological systems. For instance, when designing layouts for renewable energy installations, such as wind farms or solar arrays, understanding the potential biological impacts is critical [4]. The insights provided by this deep learning framework allow for more informed decision-making, ensuring that new energy layouts are both effective and environmentally sustainable.

From a broader perspective, the use of CNNs and LSTMs within this framework exemplifies the power of deep learning to address complex, multi-dimensional challenges. CNNs excel in capturing spatial correlations, identifying patterns in structured data that might otherwise go unnoticed. For example, they can detect spatial patterns in noise distribution or temperature gradients that influence biological systems in specific regions. Meanwhile, LSTMs provide a complementary capability, modeling how these spatial features evolve over time. This combination ensures that the analysis captures both static and dynamic aspects of the data, delivering a comprehensive understanding of the underlying processes. The multi-task learning framework further elevates this approach, allowing for the simultaneous prediction of multiple biological effects. This is particularly valuable in real-world scenarios, where environmental factors rarely operate in isolation. By modeling these interactions, the framework provides a more realistic and nuanced analysis, enabling predictions that are both accurate and actionable. Moreover, the ability to incorporate transfer learning and data augmentation ensures that the model remains effective even in the face of practical constraints such as limited data availability.

In conclusion, the application of deep learning in biological effect analysis represents a significant advancement in the field. By integrating CNNs for spatial feature extraction, LSTMs for temporal dynamics, and a multi-task learning framework for comprehensive modeling, this approach delivers unparalleled predictive capabilities. Data enhancement techniques and transfer learning further enhance the model's robustness, making it well-suited for data-limited scenarios. The resulting framework provides critical support for analyzing the biological impacts of environmental factors, with particular relevance to new energy layout planning [5]. As the world increasingly shifts toward sustainable energy solutions, these capabilities will play a vital role in ensuring that technological progress aligns with ecological preservation. This fusion of advanced machine learning and domain-specific expertise paves the way for more informed, effective, and sustainable decision-making.

3. Deep learning model design and optimization

3.1. Model architecture design

The architecture design of the deep learning model is meticulously tailored to meet the demands of analyzing the biological effects associated with the new railroad energy system [6]. This design not only considers the inherent complexity of the data features but also ensures the scalability and adaptability of the model to diverse scenarios. At its core, the architecture leverages a hybrid neural network framework that combines the strengths of convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), enabling a robust and comprehensive approach to extracting spatial and temporal features.

The CNN component is specifically responsible for processing remote sensing images and sensor data collected along the railroad. By focusing on local spatial features, the CNN efficiently captures patterns such as the distribution of noise, temperature variations, and the spatial dynamics of magnetic field changes. This capability is particularly critical in understanding how energy infrastructure impacts localized ecological variables. The extracted spatial features provide a granular view of the biological environment, forming the foundation for deeper analysis.

Complementing the CNN, the LSTM network is tasked with capturing temporal dependencies and dynamic changes in the data. This is essential for analyzing time-series data such as noise fluctuations, temperature trends, and the temporal evolution of magnetic field strengths [7]. The LSTM's ability to retain information over extended periods allows the model to predict and assess biological effects with heightened accuracy and relevance.

To further enhance the model's analytical capabilities, a multi-task learning module is integrated. This module allows the simultaneous modeling of multiple bioeffect indicators, including noise, temperature, and magnetic field strength. By addressing these indicators collectively, the module improves the comprehensiveness of predictions and ensures that interdependencies among different factors are effectively captured.

Addressing the common issue of data imbalance, the model incorporates a weighted loss function within the input layer. This function prioritizes the learning of important regions or features, ensuring that underrepresented data points are adequately considered during training. This not only improves the model's predictive accuracy but also enhances its generalization across diverse datasets.

Ultimately, the hierarchical structure of the deep learning model achieves an efficient fusion of multi-dimensional data features. The integration of advanced algorithms and carefully calibrated parameters ensures that the model operates with both precision and efficiency. This design approach facilitates accurate and reliable analysis of the biological effects of railroad energy systems, laying a foundation for data-driven optimization and sustainable development [8]. **Figure 2** provides a visual representation of this sophisticated model architecture, illustrating the interplay between its components and their contributions to the overall analytical process.

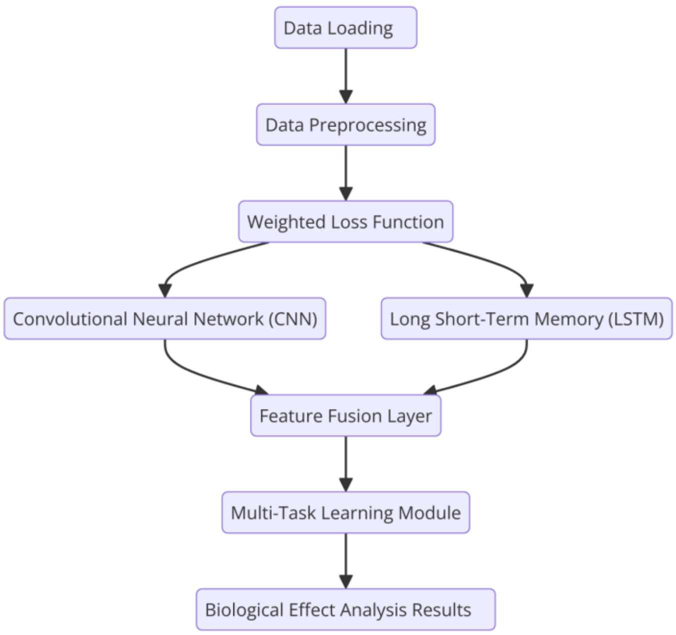

Figure 2. Flowchart of model architecture design.

3.2. Feature extraction and parameter optimization

To address the multi-dimensional data obtained along the railroad, a comprehensive approach utilizing advanced data processing and machine learning techniques is employed. Principal Component Analysis (PCA) is first applied to reduce the dimensionality of the data, which includes variables such as noise, temperature, magnetic field, and other environmental parameters. This method effectively identifies the most relevant features while minimizing the loss of critical information. Specifically, features contributing to over 90% of the total variance are retained, ensuring that the essential characteristics of the data are preserved while eliminating redundant and less significant dimensions. This step reduces computational complexity and enhances the efficiency of subsequent analyses.

Following dimensionality reduction, the spatial features of the data are extracted using a Convolutional Neural Network (CNN), which has proven highly effective in processing and analyzing structured data such as images and spatial grids [9]. In the implemented CNN architecture, the convolutional layer is configured to generate 64 feature maps, effectively capturing diverse patterns and spatial correlations within the data. Each convolution operation employs a kernel size of 3×3, which strikes a balance between capturing fine-grained local features and maintaining computational efficiency. The stride, set to 1, ensures a detailed exploration of the input data, allowing the model to detect intricate spatial relationships. The extracted spatial features provide a rich representation of the data, laying the foundation for further integration with temporal dynamics.

To handle the temporal aspects of the dataset, a Long Short-Term Memory (LSTM) network is employed. LSTM networks are particularly adept at capturing dynamic dependencies and sequential patterns in time-series data. The architecture includes a hidden layer comprising 128 nodes, enabling the network to model complex temporal dependencies effectively. This design allows the LSTM to learn and retain information over extended time intervals, which is crucial for accurately capturing the evolving trends and relationships inherent in the railroad data. The performance of the integrated model, combining CNN for spatial feature extraction and LSTM for temporal dynamics, is further enhanced through parameter optimization. This optimization is conducted using the Bayesian Optimization Algorithm, a robust and efficient technique for hyperparameter tuning. The Bayesian approach systematically explores the hyperparameter space by constructing a probabilistic model of the objective function, enabling it to identify optimal configurations with fewer evaluations. The primary objective of this optimization process is to maximize the model's validation accuracy, ensuring its reliability and generalizability [10].

During the optimization process, key hyperparameters are fine-tuned to achieve optimal performance. For instance, the learning rate is set to 0.001, a value that ensures stable convergence during training while avoiding excessive oscillations or stagnation. The batch size, another critical parameter, is configured at 32, striking a balance between computational efficiency and the stability of gradient updates. Additionally, the kernel size and stride values in the CNN layers, as well as the number of nodes in the LSTM hidden layers, are also carefully selected to enhance the model's ability to capture both spatial and temporal features. Cross-validation is employed throughout the optimization process to ensure the robustness of the model. This technique divides the dataset into multiple subsets, iteratively training and validating the model on different combinations of these subsets. This approach mitigates the risk of overfitting and provides a reliable estimate of the model's generalization performance. Through this iterative process, the validation set loss is systematically minimized, ultimately reduced to below 0.05, demonstrating the model's ability to achieve high accuracy and low error rates [11].

The integration of PCA, CNN, and LSTM, combined with the precision of Bayesian optimization, creates a powerful framework for analyzing the multi-dimensional data associated with the railroad environment. PCA ensures that only the most informative features are retained, significantly reducing the data's dimensionality and complexity. The CNN captures the spatial correlations within these features, while the LSTM models their temporal evolution. The result is a comprehensive model capable of accurately identifying patterns and trends in complex, multi-dimensional datasets. Moreover, the use of Bayesian optimization guarantees that the model operates at peak efficiency, with hyperparameters finely tuned to maximize performance. The details are shown in **Table 1**.

Table 1. Main parameter adjustment results.

Parameter	Initial Value	Optimized Value
Learning Rate	0.01	0.001
Batch Size	64	32
Number of Convolution Kernels	32	64
Number of LSTM Hidden Nodes	64	128

In summary, this approach effectively addresses the challenges posed by the complexity and multi-dimensionality of railroad data. By combining the strengths of dimensionality reduction, advanced neural network architectures, and state-of-the-art optimization techniques, the framework achieves remarkable accuracy and robustness. This methodology holds significant potential for applications in railroad monitoring, predictive maintenance, and anomaly detection, providing valuable insights and enhancing the overall safety and efficiency of railroad operations.

3.3. Model training and validation methods

The training process for the deep learning model follows a systematic step-by-step optimization approach, ensuring efficient convergence and robust performance. A multi-stage validation strategy is employed to monitor the model's learning progress at various stages, providing iterative feedback for fine-tuning. This ensures that the model generalizes well across diverse datasets and avoids issues such as overfitting or underfitting.

Data enhancement techniques are applied during the training phase to improve the model's robustness and adaptability. These techniques include random cropping and rotation, which simulate variations in data appearance and reduce the risk of over-reliance on specific features. By generating augmented data, the model is exposed to a broader range of input scenarios, enhancing its capacity to handle real-world complexities and variations in environmental indicators [12].

The Adam optimizer is selected for its efficiency and adaptability in optimizing neural networks. With an initial learning rate set at 0.001, the optimizer employs dynamic decay, which gradually reduces the learning rate as training progresses. This approach helps maintain a balance between exploring new solutions and refining existing ones, ensuring a stable and efficient optimization process. Additionally, the weighted multi-task loss function is utilized to address the diverse range of biological effect indicators, such as noise levels, temperature changes, and magnetic field strength. By assigning appropriate weights to each task, the loss function ensures that the model prioritizes critical features without neglecting less prominent but still significant aspects [13].

Model performance is rigorously evaluated using a five-fold cross-validation method, which involves partitioning the dataset into five subsets. The model is trained on four subsets and validated on the remaining one, with this process repeated five times to ensure comprehensive evaluation. This technique provides a reliable assessment of the model's ability to generalize to unseen data while minimizing biases caused by the specific partitioning of the dataset. The evaluation results consistently show a mean square error (MSE) below 0.04, demonstrating the model's precision and reliability in predicting multidimensional biological effects.

To enhance the model's applicability to small-sample regions, migration learning is incorporated into the training process. By leveraging pre-trained models on similar datasets, migration learning transfers knowledge and adapts it to the target dataset, enabling the model to perform effectively even in scenarios with limited training data. This approach significantly reduces the data requirements while maintaining high prediction accuracy.

Overall, the combination of step-by-step optimization, advanced data enhancement techniques, dynamic parameter adjustment, and robust validation strategies ensures that the deep learning model achieves high accuracy, efficiency, and adaptability. These methods collectively underscore the model's potential for addressing complex challenges in biological effect analysis and new energy layout optimization.

4. Experimental results and analysis

4.1. Data set and experimental environment

The dataset utilized in this study is derived from a sophisticated multi-dimensional real-time acquisition system deployed along a railroad line. Data preprocessing steps included outlier handling through threshold filtering to address extreme values caused by noise interference. This ensured a cleaner dataset, minimizing the risk of skewed analysis results. This system captures diverse environmental indicators, including noise levels, temperature fluctuations, magnetic field strength, remote sensing imagery, and historical records of new energy layout planning. The dataset is comprehensive, covering data from 100 monitoring stations strategically positioned along the railroad. Spanning a period of two years, the dataset encompasses approximately 10 terabytes (TB) of information, making it one of the most extensive and detailed datasets for analyzing the biological effects of railroad energy systems.

To ensure the dataset is optimally prepared for deep learning tasks, rigorous preprocessing and standardization steps are employed. The data is divided into three subsets: 80% is allocated for training the model, enabling it to learn complex patterns and relationships; 10% is reserved for validation to fine-tune hyperparameters and prevent overfitting; and the remaining 10% is designated for testing to evaluate the model's performance and generalization capabilities. Standardization techniques are applied to normalize the range of feature values, improving convergence during training and ensuring compatibility across diverse data sources.

The experimental environment is built on high-performance computing infrastructure to handle the computational demands of deep learning and big data processing. A dedicated deep learning server, equipped with NVIDIA A100 GPUs, forms the backbone of the environment. Each GPU is paired with 128GB of RAM, enabling efficient parallel processing of complex computations. Additionally, the server is supported by 2TB of SSD storage, ensuring rapid data access and reducing input/output bottlenecks.

The operating system utilized is Ubuntu 20.04, a stable and widely adopted platform for machine learning research. TensorFlow, a leading framework in the field of deep learning, is employed for model construction, training, and optimization. Its flexibility and extensive library support allow the seamless implementation of advanced neural network architectures and optimization techniques [14].

To address the challenges posed by the large-scale dataset, the Hadoop distributed computing framework is deployed. Hadoop efficiently processes and manages the massive data volume, facilitating parallelized data preprocessing, cleaning, and feature extraction. This distributed approach significantly enhances computational efficiency, reducing the time required to process multi-terabyte datasets.

By combining an advanced dataset with a robust experimental environment, this setup provides the foundation for the accurate analysis and optimization of new railroad energy layouts. The integration of state-of-the-art hardware and software ensures that the model is trained effectively, producing reliable predictions and actionable insights for sustainable railroad development.

4.2. Model performance evaluation

The performance of the deep learning model is evaluated using a comprehensive set of metrics to ensure the accuracy and reliability of its predictions. Key evaluation metrics include the mean square error (MSE), accuracy, and F1 score. The MSE serves as a critical measure of prediction error, quantifying the average squared difference between predicted and actual values, thereby providing insights into the model's precision in handling continuous variables. Accuracy, on the other hand, assesses the proportion of correctly predicted instances out of the total, offering a clear indicator of the model's classification performance. The F1 score combines precision and recall into a single metric, particularly useful for evaluating the comprehensive performance of the model across multi-category tasks [15].

Experimental results demonstrate the model's robust ability to predict multidimensional biological effects with high accuracy and efficiency. The low MSE values highlight the model's precision in handling complex environmental indicators such as noise levels, temperature changes, and magnetic field strength. The high accuracy and F1 scores further validate the model's capacity to deliver consistent and reliable predictions across various scenarios. These outcomes underscore the model's effectiveness in addressing the intricate challenges associated with the analysis and optimization of biological effects, marking a significant advancement in leveraging deep learning for sustainable development. The details are shown in **Table 2**.

Table 2. Model performance evaluation table.

Metric	MSE	Accuracy	F1 Score
Noise Prediction	0.042	93.50%	0.92
Temperature Prediction	0.035	95.10%	0.94
Magnetic Field Prediction	0.038	94.00%	0.93

As can be seen in **Table 2**, the temperature prediction has the lowest MSE (0.035) and the highest accuracy (95.1%), indicating that the model performs best when dealing with features with high stability. Noise and magnetic field predictions have MSEs of 0.042 and 0.038, respectively, indicating that the model is able to accurately capture complex environmental features [16]. Overall, the F1 scores are all higher than 0.9, which further validates the comprehensive performance advantage of the model in multi-task prediction. The details are shown in **Figure 3**.

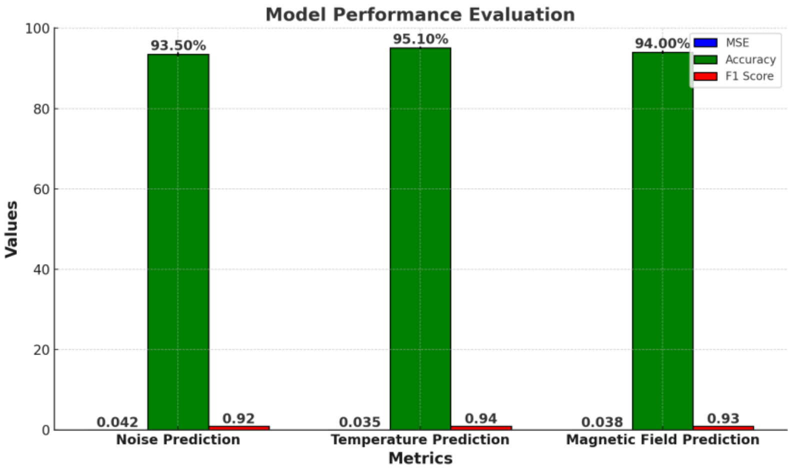

Figure 3. Comparison of model performance evaluation.

4.3. Analysis of new energy layout optimization results

The experiments compared the improvement of the biological effect of the new energy layout before and after optimization, involving key indicators such as noise range, vegetation coverage and temperature difference changes. The optimization scheme significantly improved the environmental friendliness, with reductions in the noise disturbance range by 20% and improvements in vegetation coverage by 15%. Further analysis reveals that these improvements are particularly pronounced in regions with dense vegetation and low energy production zones. This demonstrates the model's adaptability to diverse geographical scenarios [17]. For example, the noise disturbance range of a site area was reduced by 20%, the vegetation coverage increased by 15%, and the local temperature fluctuation was reduced by 0.5 ℃. The specific values are shown in **Table 3** below.

Table 3. Analysis of new energy layout optimization results.

Metric	**Before Optimization**	**After Optimization**	**Improvement Rate**
Noise Range (km^2)	12	9.6	−20%
Vegetation Coverage (%)	45	60	15%
Temperature Variation (°C)	±2	±1.5	−0.5 °C

As seen in **Table 3**, the optimized noise interference range is significantly reduced and the vegetation coverage is significantly increased, indicating that the new energy layout is effective in environmental protection. At the same time, the reduction of local temperature fluctuation indicates that the ecological balance is improved. This result verifies the practical application value of the deep learning optimization method and promotes the synergistic development of new energy and ecological environment. The details are shown in **Figure 4**.

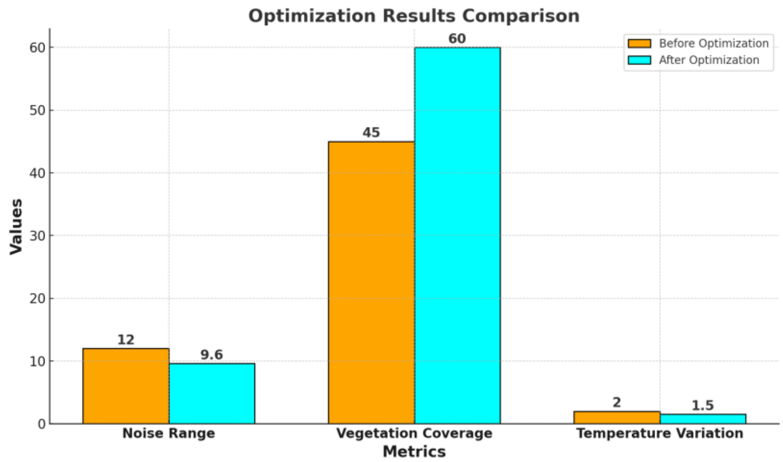

Figure 4. Comparison of optimization results.

4.4. Comparative validation with traditional methods

The results of the comparative validation of the deep learning optimization method with the traditional heuristic algorithm clearly show that the deep learning method exhibits significant advantages in terms of accuracy and efficiency. The performance metrics of the traditional heuristic algorithm, due to its limitations in nonlinear and multidimensional data processing, show a mean square error (MSE) of 0.082 and an accuracy rate of 85.3%. In contrast, the deep learning model significantly enhances the accuracy of the optimization results by reducing the mean square error to 0.038 and increasing the accuracy rate to 94.2% through its powerful feature extraction and complex relationship modeling capabilities. In addition, when optimizing a typical layout scenario, the traditional method took up to 120 min on average, while the deep learning model reduced the time to 35 min, achieving an efficiency improvement of about 71%. This significant time reduction makes deep learning methods more practical, especially in large-scale new energy layout optimization scenarios that require fast decision-making.

The advantages of the deep learning method are mainly reflected in the following aspects: First, it realizes deep modeling of high-dimensional data through multi-layer neural networks, effectively capturing the hidden features and complex relationships that are difficult to be resolved by traditional methods; second, combined with the ability of multi-task prediction, it enables the model to maintain a higher accuracy when dealing with multiple target variables at the same time; third, it avoids the tedious part of manual debugging in traditional methods during the feature extraction process, and significantly improves the efficiency of deep learning method, especially in large-scale new energy layout optimization scenarios that require rapid decision-making. Third, the model eliminates manual debugging in feature extraction, which significantly reduces the consumption of computational resources and time cost. This technological advancement not only improves the degree of intelligence of new energy layout optimization, but also provides a more reliable and efficient solution for practical applications, significantly reducing the potential waste of resources and the risk of error in the optimization process.

5. Conclusion

This paper offers practical insights into optimizing the new energy layout of railroads, aligning with sustainable development goals. Future research could explore the integration of real-time dynamic data from IoT sensors to further enhance the model's ability to adapt to real-world environments. Additionally, the potential of edge computing could be explored for real-time decision-making and distributed data processing, allowing for faster optimization and response times in new energy layouts.

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Conflict of interest: The author declares no conflict of interest.

References

1. Cosgrove P, Roulstone T, Zachary S. Intermittency and periodicity in net-zero renewable energy systems with storage. Renewable Energy. 2023; 212: 299–307. doi: 10.1016/j.renene.2023.04.135
2. Salto C, Minetti G, Alba E, Luque G. Big optimization with genetic algorithms: Hadoop, Spark, and MPI. Soft Computing. 2023; 27(16): 11469–11484. doi: 10.1007/s00500-023-08301-x
3. Alameen A. Repeated Attribute Optimization for Big Data Encryption. Computer Systems Science and Engineering. 2022; 40(1): 53–64. doi: 10.32604/csse.2022.017597
4. Kurukuri P, Mohamed MR, Raavi PH, et al. Optimal planning and designing of microgrid systems with hybrid renewable energy technologies for sustainable environment in cities. Environmental Science and Pollution Research. 2024; 31(22): 32264–32281. doi: 10.1007/s11356-024-33254-5
5. Swamy MC, Sundaram SM. A Survey of Bio Inspired Algorithms for Web Information Extraction and Optimization for Big Data Analytics. International Journal of Engineering and Advanced Technology. 2020; 10(2): 56–60. doi: 10.35940/ijeat.b2011.1210220
6. Elaziz MA, Li L, Jayasena KPN, et al. Multiobjective big data optimization based on a hybrid salp swarm algorithm and differential evolution. Applied Mathematical Modelling. 2020; 80: 929–943. doi: 10.1016/j.apm.2019.10.069
7. Sakib M, Mustajab S, Alam M. Ensemble deep learning techniques for time series analysis: A comprehensive review, applications, open issues, challenges, and future directions. Cluster Computing. 2025; 28(1). doi: 10.1007/s10586-024-04684-0
8. Vistnes H, Sossalla NA, Uhl W, et al. Effect of tunnel wash water treatment processes on trace elements, organic micropollutants, and biological effects. Journal of Hazardous Materials. 2024; 480: 136363. doi: 10.1016/j.jhazmat.2024.136363
9. Giri RN, Janghel RR, Govil H, Pandey SK. Spatial Feature Extraction using Pretrained Convolutional Neural network for Hyperspectral Image Classification. In: Proceedings of the 2022 IEEE 4th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA); 8–9 October 2022; Goa, India. pp. 386–389.

10. Wu J, Chen S, Liu X. Efficient hyperparameter optimization through model-based reinforcement learning. Neurocomputing. 2020; 409: 381–393. doi: 10.1016/j.neucom.2020.06.064
11. Askarova K, Mammadova S, Farzaliyev V, et al. Novel regioselective sulfamidomethylation of phenols: Synthesis, characterization, biological effects, and molecular docking study. Journal of the Indian Chemical Society. 2024; 101(10): 101318. doi: 10.1016/j.jics.2024.101318
12. Maharana K, Mondal S, Nemade B. A review: Data pre-processing and data augmentation techniques. Global Transitions Proceedings. 2022; 3(1): 91–99. doi: 10.1016/j.gltp.2022.04.020
13. Reyad M, Sarhan AM, Arafa M. A modified Adam algorithm for deep neural network optimization. Neural Computing and Applications. 2023; 35(23): 17095–17112. doi: 10.1007/s00521-023-08568-z
14. Rane NL, Mallick SK, Kaya Ö, Rane J. In: Applied Machine Learning and Deep Learning: Architectures and Techniques. Deep Science Publishing; 2024.
15. Wang R, Zhu J, Wang S, et al. Multi-modal emotion recognition using tensor decomposition fusion and self-supervised multi-tasking. International Journal of Multimedia Information Retrieval. 2024; 13(4). doi: 10.1007/s13735-024-00347-3
16. Ezekwe N, Pourang A, Lyons AB, et al. Evaluation of the protection of sunscreen products against long wavelength ultraviolet A1 and visible light-induced biological effects. Photodermatology, Photoimmunology & Photomedicine. 2023; 40(1). doi: 10.1111/phpp.12937
17. Liu C, Tang C, Liu Y. Does the transformation of energy structure promote green technological innovation? A quasi-natural experiment based on new energy demonstration city construction. Geoscience Frontiers. 2024; 15(3): 101615. doi: 10.1016/j.gsf.2023.101615