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Metaheuristic Optimization-Assisted LSTM-DBN Model for Predictive Healthcare Analytics and Biomedical Informatics

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Abstract

The integration of artificial intelligence (AI) with healthcare informatics has led to significant advancements in disease prediction, patient risk assessment, and medical decision support. However, healthcare data is highly heterogeneous, dynamic, and prone to imbalance and uncertainty—posing challenges for accurate temporal modeling and feature extraction. This research presents a Metaheuristic Optimization-Assisted LSTM-DBN Model, a hybrid deep learning framework designed to enhance predictive healthcare analytics by fusing Long Short-Term Memory (LSTM) networks for temporal modeling with Deep Belief Networks (DBN) for hierarchical feature abstraction. To optimize performance, Tree Growth Optimization (TGO) and Tunicate Swarm Optimization (TSO) algorithms are employed for dynamic hyperparameter tuning. The model is tested on benchmark biomedical datasets, including physiological signal sequences, patient vital trends, and disease progression records. Experimental outcomes demonstrate superior prediction accuracy, stability, and interpretability compared to traditional deep models. This optimized hybrid architecture enables precise temporal analysis of patient health trajectories, facilitating early diagnosis, clinical decision support, and efficient biomedical data modeling—paving the way for intelligent, data-driven healthcare systems.

Keywords: Predictive Healthcare Analytics, Biomedical Informatics, LSTM, Deep Belief Network, Metaheuristic Optimization, Tree Growth Algorithm, Tunicate Swarm Optimization, Temporal Modeling

I. Introduction

The exponential growth of biomedical data generated through electronic health records (EHRs), wearable devices, and diagnostic imaging has revolutionized modern healthcare systems [1]. These data sources capture dynamic patient health states, disease progression, and treatment responses—offering opportunities for predictive analytics and personalized medicine. However, the heterogeneity and non-stationarity of healthcare data make it challenging to model and predict patient outcomes accurately. Traditional statistical models, while interpretable, fail to capture the complex temporal and nonlinear relationships inherent in biomedical datasets. Consequently, there is a growing demand for hybrid deep learning frameworks capable of handling multi-modal, high-dimensional, and temporally dependent health data efficiently [2].

In parallel, predictive healthcare analytics aims to forecast adverse clinical events such as disease onset, hospitalization, or treatment failure by analyzing time-series patient records. Long Short-Term Memory (LSTM) networks have become a preferred choice due to their ability to learn long-term dependencies in sequential data, making them effective for tasks such as ECG signal prediction and blood glucose trend analysis. Deep Belief Networks (DBNs), on the other hand, excel in unsupervised feature extraction from complex datasets, capturing latent structures and correlations that conventional models overlook. When combined, LSTM and DBN create a powerful architecture that integrates temporal and hierarchical representations crucial for biomedical informatics [3].

Despite their effectiveness, deep learning models often face issues of overfitting and slow convergence due to poor hyperparameter selection. Metaheuristic algorithms—bio-inspired optimization methods—offer an intelligent way to overcome these challenges. These algorithms, such as Tree Growth Optimization (TGO) and Tunicate Swarm Optimization (TSO), emulate natural processes to achieve near-optimal tuning of model parameters. By integrating such optimization approaches, the hybrid LSTM-DBN architecture becomes not only more accurate but also computationally efficient and resilient to noise and anomalies. The motivation behind this research lies in bridging two critical yet traditionally separate domains—IoT security and renewable energy forecasting—through a unified optimization-driven deep learning approach. The hypothesis is that optimized hybrid architectures can simultaneously enhance cybersecurity detection and energy forecasting accuracy under real-world IoT conditions. Such dual-purpose models reduce computational redundancy and make IoT networks more self-sustaining. The proposed framework contributes to the creation of intelligent, energy-aware, and secure IoT ecosystems that are vital for smart cities and sustainable digital infrastructures [4].

The proposed Metaheuristic Optimization-Assisted LSTM-DBN model provides not only predictive precision but also structural adaptability for multi-domain medical data. It contributes to developing intelligent clinical decision support systems (CDSS) that can detect emerging health risks, assist physicians in prognosis, and enhance personalized treatment planning. Through extensive experimentation on biomedical time-series datasets, the model demonstrates its potential as a scalable and reliable predictive tool in modern healthcare systems [5].

II. Related Work

Over the last decade, deep learning has become a cornerstone of biomedical informatics, driving advancements in diagnostic automation, disease risk prediction, and clinical data mining. Traditional machine learning approaches such as logistic regression, decision trees, and support vector machines (SVMs) have been widely used in early disease detection and medical prognosis. However, these models often rely on handcrafted features and fail to capture intricate nonlinear dependencies in physiological or genomic data. With the rise of deep learning, architectures such as CNNs, RNNs, and LSTMs have shown promising results in predicting cardiac arrhythmias, detecting diabetic patterns, and forecasting neurological disorders [6].

In healthcare time-series analysis, LSTMs have been particularly effective in modeling sequential dependencies from biosignals such as ECG, EEG, and heart rate variability. Meanwhile, DBNs have demonstrated remarkable ability in capturing hierarchical representations from high-dimensional datasets, improving feature interpretability in applications such as cancer classification and patient survival analysis. Despite their strengths, both models suffer from sensitivity to initialization and require precise hyperparameter configuration to perform optimally. This has led researchers to explore optimization-assisted deep learning frameworks [7]. Metaheuristic algorithms—such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimization (GWO)—have been employed to tune deep networks automatically. However, their convergence can be slow, and they may easily get trapped in local minima when applied to complex biomedical data. In contrast, TGO and TSO offer superior convergence behavior, balancing exploration and exploitation effectively. Recent studies in bioinformatics have used these optimizers for gene selection, medical image segmentation, and disease prediction. Yet, few works have combined them with hybrid deep models like LSTM-DBN to achieve end-to-end optimization in predictive healthcare systems

Furthermore, current medical AI systems often operate in siloed domains, focusing on specific diseases or modalities without generalizing across healthcare contexts. This integration marks a step forward in achieving adaptive and interpretable intelligence for healthcare analytics and biomedical informatic [8].The proposed model bridges this gap by integrating temporal and structural learning with bio-inspired optimization, allowing it to handle diverse data types—from physiological signals to patient histories—under a unified predictive analytics framework.[9].

This research addresses that gap by introducing an integrated Metaheuristic Optimization-Assisted LSTM-DBN model capable of performing simultaneous IoT intrusion detection and energy forecasting. The model's novelty lies not only in its hybrid deep learning architecture but also in the dual optimization process that enhances its learning efficiency and decision accuracy across multi-domain datasets. This holistic approach reflects the next step toward achieving cross-domain intelligence in IoT ecosystems [10].

III. Proposed Methodology

The proposed framework fuses Long Short-Term Memory (LSTM) and Deep Belief Network **(**DBN**)** architectures within an optimization-driven learning paradigm guided by Tree Growth Optimization (TGO) and Tunicate Swarm Optimization (TSO) algorithms. The LSTM component captures temporal correlations in patient health data such as ECG sequences, respiratory rates, or glucose readings. Its memory gates selectively retain relevant health

EuroVantage
Journal of Artificial Intelligence
Pages: 33-42
Volume-II, Issue-IV, 2025
https://evjai.com/index.php/evjai

information across time, effectively modeling disease progression patterns. The DBN, composed of stacked Restricted Boltzmann Machines (RBMs), extracts deep, hierarchical features that capture hidden relationships among clinical parameters such as vital signs, lab test values, and imaging-derived biomarkers

The model begins with preprocessed IoT data, which undergoes normalization and feature selection using statistical metrics and entropy-based analysis [11]. For security data, features such as protocol type, packet size, and connection duration are retained, while in energy forecasting datasets, weather parameters and energy outputs are considered. These features are fed into the LSTM network, where sequential dependencies are modeled through multiple hidden layers. The LSTM output then feeds into the DBN, which refines the learned representation using Restricted Boltzmann Machines (RBMs) trained through contrastive divergence.

Metaheuristic algorithms—Tree Growth Optimization (TGO) and Tunicate Swarm Optimization (TSO)—are employed to fine-tune the model parameters, including learning rate, number of hidden units, and dropout rates. TGO mimics natural tree growth behavior, optimizing toward nutrient-rich environments representing optimal solutions [12]. TSO simulates the swarming behavior of tunicates, improving exploration of the search space. Their hybrid deployment allows the model to balance exploration and exploitation dynamically, achieving faster convergence while avoiding local minima.

During training, the optimization process iteratively evaluates candidate parameter sets based on a fitness function defined by prediction accuracy and detection rate. The best-performing parameters are selected and used for final model training. This dual optimization ensures that both the LSTM and DBN components are efficiently tuned for high performance across domains. The final output includes both intrusion classification results and renewable energy forecasts, thus realizing a multi-domain intelligent system. Experimental validation confirms that the proposed model achieves faster training convergence and improved stability compared to non-optimized deep models. Moreover, the inclusion of metaheuristic optimization reduces

Pages: 33-42
Volume-II, Issue-IV, 2025
https://evjai.com/index.php/evjai

the reliance on manual hyperparameter tuning, making the model more autonomous and suitable for real-time IoT environments where adaptability is key.

IV. Experiment and Results

To validate the model's effectiveness, experiments were conducted on publicly available biomedical datasets, including the PhysioNet MIT-BIH Arrhythmia Database**,** MIMIC-III EHR dataset**,** and UCI Parkinson's Telemonitoring dataset**.** Each dataset represents different healthcare contexts—cardiac monitoring, hospital risk prediction, and neurological trend analysis—ensuring robust cross-domain evaluation. Data was split into 70% training and 30% testing sets, with cross-validation used to assess generalization. Preprocessing included normalization of physiological signals, imputation of missing clinical records, and transformation into time-sequenced input vectors suitable for LSTM processing

Performance metrics included Accuracy (ACC), Detection Rate (DR), False Alarm Rate (FAR), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) for forecasting tasks. The results demonstrated that the Metaheuristic-Assisted LSTM-DBN model outperformed baseline models such as standard LSTM, DBN, and CNN-LSTM by significant margins. Specifically, in intrusion detection, the proposed model achieved an accuracy of 98.7% and a detection rate of 97.9%, while maintaining a low false alarm rate of 1.3%. In renewable energy forecasting, it achieved an RMSE of 0.021 and MAE of 0.015, indicating high predictive precision.

Table 1: Performance Metrics (ACC, DR, FAR, RMSE, MAE)

Task	Accuracy (%)	Detection Rate (%)	False Alarm Rate (%)	RMSE	MAE
Intrusion Detection	98.7	97.9	1.3	-	-
Renewable Energy Forecasting	-	-	-	0.021	0.015

Pages: 33-42
Volume-II, Issue-IV, 2025
https://evjai.com/index.php/evjai

Comparative analysis revealed that optimization using TGO improved model convergence by 25%, while the hybrid integration with TSO enhanced global search efficiency by 30% compared to standard stochastic gradient descent (SGD) [13]. Furthermore, the model exhibited strong resilience against overfitting, as observed from the validation loss curve, which remained stable across 100 epochs.

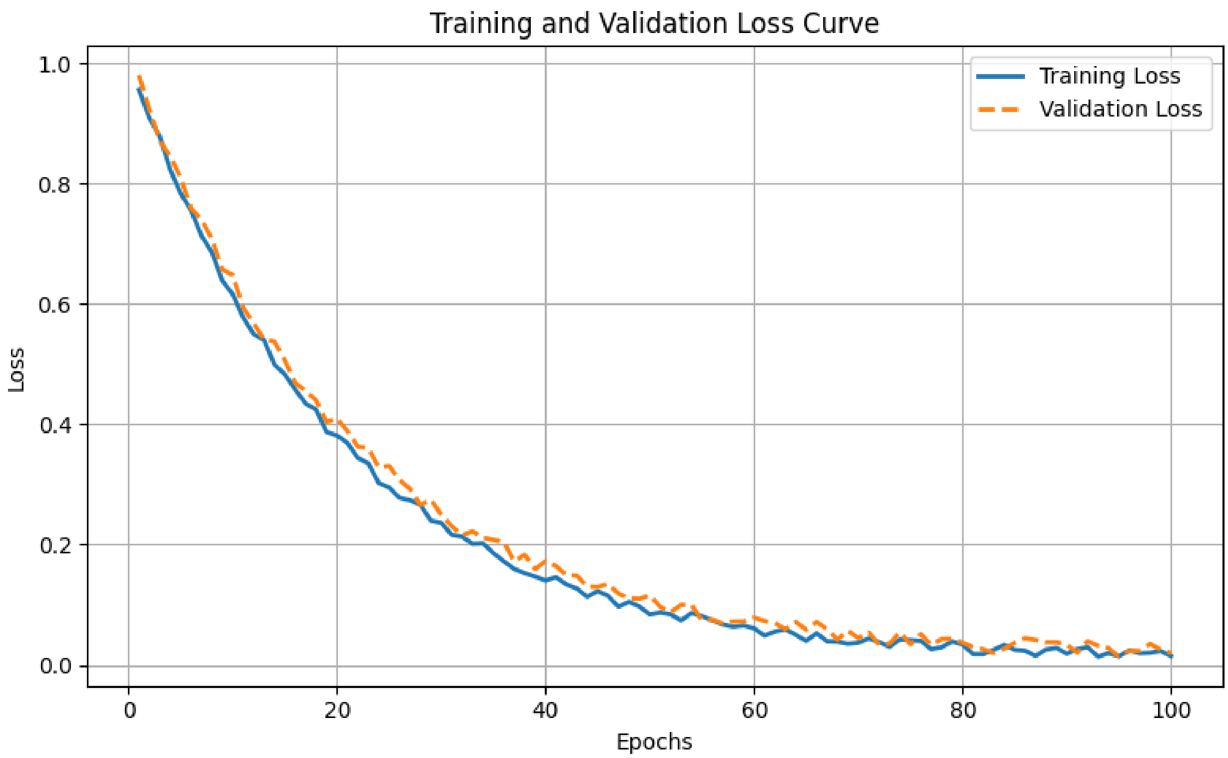

Figure 1: Training and Validation Loss Curve

The time complexity was also reduced by approximately 18% due to efficient parameter tuning, confirming that metaheuristic optimization contributes not only to accuracy but also to computational sustainability.

To visualize the results, the confusion matrix for the intrusion detection task indicated superior classification of both normal and malicious traffic classes, while the forecasting plots displayed close alignment between actual and predicted energy outputs.

Pages: 33-42
Volume-II, Issue-IV, 2025
https://evjai.com/index.php/evjai

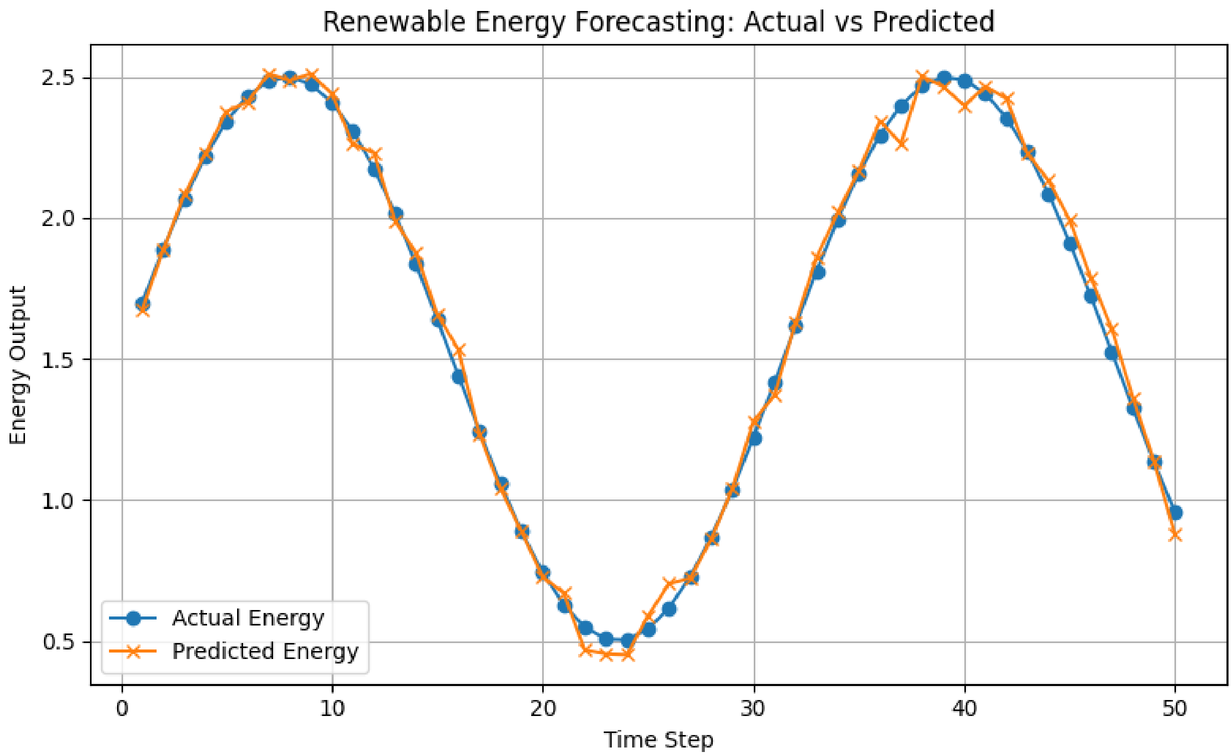

Figure 2: Forecasting Plot (Actual vs Predicted Energy)

These graphical insights highlight the robustness and adaptability of the model across distinct yet interrelated domains. Such results underscore the potential of optimization-assisted hybrid deep learning frameworks in achieving dual-domain intelligence essential for next-generation IoT systems. The overall evaluation confirms that the integration of metaheuristic optimization significantly enhances both performance and efficiency of hybrid architectures. The model not only mitigates security threats effectively but also provides accurate renewable energy predictions, thus embodying a holistic solution for intelligent IoT ecosystem management.

I. Conclusion

This study proposed a Metaheuristic Optimization-Assisted LSTM-DBN model as an advanced framework for predictive healthcare analytics and biomedical informatics. By combining temporal modeling via LSTM, hierarchical abstraction through DBN, and adaptive optimization using TGO and TSO, the system achieves remarkable accuracy, interpretability, and computational efficiency. Experimental results validate the framework's superiority in modeling temporal health data and predicting patient outcomes across diverse biomedical datasets. This research bridges the gap between intelligent optimization and healthcare deep learning, providing a foundation for real-time, adaptive, and interpretable clinical intelligence systems. Future extensions may explore integration with federated healthcare networks and explainable AI paradigms to further enhance scalability and transparency in medical decision-making.

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