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A Multi-Stage Hybrid Architecture Integrating, Transformer-Based Deep Learning, and Reinforcement Learning for Adaptive Feature Extraction and Classification of Noisy Biosensor Time-Series Data

Dr. Geetha T V[1], Dr Vijesh Krishnamoorthy[2], Abha Kiran Rajpoot[3], Dr.Aravindan Srinivasan[4], R. Naveenkumar[5], Ali Bostani[6], Tarandeep Singh Walia[7], Deepender[8]

[1]Assistant Professor, Department of IOT-CSBS/SCSE, SRM Institute of Science and Technology, Ramapuram, Chennai. Email: geethatv.1309@gmail.com, Orchid ID: 0000-0002-4809-4996

[2]Chair - Information Technology and Computer Science, Department of Information Technology and Computer Science, Innovative Universities of Enga,Papua New Guinea. Email:kvijesh@iue.ac.pg, https://orcid.org/0000-0001-9473-7553

[3]School of Computer Science & Engineering, Galgotias University, Greater Noida ,Uttar Pradesh, India. Email ID: akrajpoot@gmail.com, Orchid ID: 0000-0002-0643-3646

[4]Department of computer science and Engineering, Koneru Lakshmaiah Education foundation, Vaddeswaram, Andhra Pradesh, India. Email: kkl.aravind@kluniversity.in, 0000-0001-5482-7351

[5]Dept of CSE, School of Engineering and Technology, CGC University Mohali-140307, Punjab India. Email: drnk1983@gmail.com, 0000-0001-9033-9400

[6]Associate Professor, College of Engineering and Applied Sciences, American University of Kuwait, Salmiya, Kuwait. Email: abostani@auk.edu.kw, 0000-0002-7922-9857

[7]Associate Professor, School of Computer Applications, Lovely Professional University, Phagwara, Punjab, India. Email: taran_walia2k@yahoo.com, Orcid id:- https://orcid.org/0000-0001-8127-3112

[8]Research Scholar, School of Computer Applications, Lovely Professional University, Phagwara, Punjab, India. Email: deependerduhan6@gmail.com, Orcid I'd:0000-0002-0529-4007

*Corresponding Author: Rustam Jumayev, E-mail: rjumayev@buxdu.uz; rustamjumayev850@gmail.com

Abstract

The successful application of biosensor technologies in healthcare monitoring has created massive time-series data which are often distorted by noise, motion sources and environmental interference. Current machine learning and deep learning solutions tend to miss the ability to simultaneously feature localized signal properties, temporal dynamics on a long-range scale, and the ability to adapt to noise robustness. To solve these issues, the paper will suggest a multi-phase hybrid architecture to include Convolutional Neural Networks (CNNs), Transformer-based deep learning, and Reinforcement Learning (RL) in adaptive feature extraction and classification of noisy biosensor time-series data. The CNN module learns a discriminative local features, and the Transformer learns global temporal dependencies with self-attention mechanisms. A layer of RL-based optimization is presented that refines feature representations dynamically by adapting to changing noise levels by weighting and selecting, as well as by changing the noise levels. The suggested framework is tested on benchmark biosensor signals, both ECG and wearable sensor signals, in synthetic noise and real noise conditions. The experimental results show that the proposed model provides better performance: the accuracy of 95.7, F1-score of 95.2, and AUC of 0.97 are better than the traditional CNN, Transformer, and hybrid baselines. In addition, the RL component is highly robust to high noise. The proposed architecture offers a scalable and smart mechanism of real-time biosensor data analytics in the next-generation healthcare systems.

Keywords:

Biosensor time-series data, convolutional neural networks (CNN), Transformer, reinforcement learning (RL), adaptive feature extraction, noisy signal classification, healthcare analytics, deep learning, temporal modeling, signal processing.

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1. Introduction

Biosensor-based systems have turned into one of the pillars of contemporary healthcare, with the ability to continuously record physiological indicators including electrocardiograms (ECG), electroencephalograms (EEG), and wearable sensor data. These systems produce high-dimensional time-series data that are vital in the early diagnosis and instant health monitoring. Nevertheless, the nature of biosensor signals is susceptible to noise, motion artifacts, baseline drift and environmental interference that severely impair the quality of signals and negatively impact the quality of downstream analytics [1]-[3]. Such strong and dynamic signal processing methods are thus critical in guaranteeing sound interpretation of such data. Traditional machine learning models and classical signal processing models tend to use hand-designed features and to not scale to high levels of noise [4]-[6]. Recent developments in deep learning have also exposed the use of Convolutional Neural Networks (CNNs) to learn automated feature extraction, which has shown good results in the ability to pick up local spatial and temporal features in biosensor signals [7]-[8]. Nonetheless, CNNs have localized receptive fields that inherently restrict their ability to capture long-range dependencies in their models. To address this shortcoming, Transformer-based models have been used on time-series sequence, and utilize self-attention to learn global temporal dependencies [9]-[11]. Transformers, although having benefits, are computationally expensive, noise-sensitive and heavy on large scale data to train efficiently [8]. Of greater significance, current deep learning architectures do not have the flexibility to actively optimize feature representations when the noise, and signal conditions change. The possible solution to the learning of the optimal feature selection and weighting strategies in dynamic environment is Reinforcement Learning (RL) that has demonstrated promising results in sequential decision-making and adaptive control problems [12], [13].

But little effort has been made in integrating RL with deep learning frameworks to extract adaptive features in the analysis of biosensor time-series.

To overcome these drawbacks, this paper suggests a multi-step hybrid system that would combine CNN, Transformer and Reinforcement Learning to achieve a resilient and adaptive feature extraction and classification of biosensor time-series data in the presence of noise. The suggested framework uses CNNs to extract local features, Transformers to model global time, and an adaptive feature refinement optimization layer using RL. Experimental validation of the model shows better classification accuracy, strength and flexibility than the baseline models.

2. Related Work

The time-series analysis in biosensors has been based on the application of statistical signal processing methods and classical machine learning algorithms like support vector machines and random forests. Although these techniques offer baseline performance, they are very reliant on hand-crafted feature extraction, and fail to perform well with nonlinear patterns and high noise variability that occur in biosensor data in the real world [14], [15]. As a result of the development of deep learning, Convolutional Neural Networks (CNNs) have found widespread use in the biomedical signal analysis domain because of their capability to learn hierarchical feature representations automatically. CNN-based solutions have shown great performance in ECG classification, analysis of EEG signal, and wearable sensor data processing [16], [17]. Nevertheless, CNNs mainly deal with local receptive areas and have a poor ability to learn long-term temporal relationships, which restricts their capabilities on higher order sequential modeling tasks [18]. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks were proposed to solve these shortcomings, and are applied to temporal modeling. These models are effective but have problems of vanishing gradients and a lack of parallelization [19]. More recently, time-series analysis with Transformer-based architectures has attracted much attention due to the use of self-attention mechanisms to capture global dependencies without repetition [20]. Transformers, although with these benefits, are computationally expensive, and they are also sensitive to noisy inputs especially when the signal-to-noise ratio is low [21]. Reinforcement Learning (RL) has been extensively studied in healthcare in areas like treatment planning, resource allocation, and adaptive control systems [22]. Nevertheless, it has little use in adaptive time-series feature extraction, and noise-conscious optimization of biosensor data. Current methods do not often combine RL with deep neural networks to pick or bias features dynamically in the presence of noise. Even though hybrid deep learning models such as CNNs and Transformers have demonstrated better mind-reading on select time-series tasks, they do not come with adaptable mechanisms to learn applications with diverse noise environments [23]. Little has been done to date to integrate CNN, Transformer, and RL into a single adaptive feature optimization framework in noisy biosensor settings.

As such, a serious research gap lies in creating a robust and adaptive noise-resistant framework whereby local feature extraction, global temporal modelling and dynamic optimization strategies are jointly utilized. To fill this gap, this paper proposes a multi-stage hybrid architecture that combines CNN, Transformer, and Reinforcement Learning to achieve better biosensor time-series analysis.

3. Proposed Methodology

3.1 Overview of Architecture

This proposed study presents a multi-stage hybrid framework aimed at overcoming the limitations of noisy biosensor time-series data to extract convolutional features, model time-series by attention, and optimise adaptively using a reinforcement learning algorithm. The general architecture can be seen as a sequence of steps where raw biosensor signals are processed initially to reduce the effects of noise and normalise distributions of inputs. These processed signals are then subjected to a Convolutional Neural Network (CNN) to identify localized features that are able to detect short-term variations and inherent signal properties. These characteristics are then trained in a Transformer-based network to understand long-range temporal and contextual relationships across the world. Lastly, a Reinforcement Learning (RL) agent is added to dynamically optimize the feature representations by dynamically choosing or weighting features depending on noise conditions and classification performance. The refined features are then sent to a classification-layer to make a final decision. This unified solution will provide robustness, flexibility, and a better classification capability in different signal conditions. Fig. 1 provides the general structure of the proposed multi-level hybrid framework.

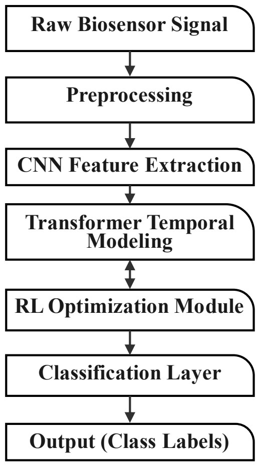

Figure 1. Overall Architecture of the Proposed Multi-Stage Hybrid Framework

3.2 Data Preprocessing

A biosensor time-series signal is the input to the system expressed as,

$$X = \{x_1, x_2, \dots, x_T\} \quad (1)$$

where Tdenotes the temporal length of the signal. In the real life situation, biosensor data suffer due to many kinds of noise such as Gaussian noise, motion artifacts, and environmental disturbances. This is modeled as,

$$X_{noisy} = X + N \quad (2)$$

where Nrepresents the noise component.

A preprocessing step is used to normalise and standardize the signal to obtain a reliable feature extraction. Normalization transforms the input data to a steady range which has less variation between samples and enhances convergence in training. Moreover, optional baseline filtering methods can be used to remove noise content in high frequencies, e.g. bandpass filtering or smoothing. The time-series signal (continuous) is then divided into overlapping (or non-overlapping) windows of fixed length that allows the signal to be efficiently processed in batches and time dynamics to be examined in localized contexts. This division also enables a match to deep learning models in which the input must have fixed size.

3.3 CNN-Based Feature Extraction

After preprocessing, the noisy input signal is passed through a Convolutional Neural Network (CNN) to obtain discriminative local features. The CNN makes use of a sequence of convolution steps which learn spatial and temporal features directly based on the input data. The extraction of the features can be mathematically illustrated as shown below,

$$F_c = CNN(X_{noisy}) \_\_\_\_\_\_\_\_\_\_\_\_\_\_ (3)$$

where $F_c$denotes the set of learned feature maps.

A convolutional layer uses a collection of learnable filters on the input signal, computing response features by doing the operation.,

$$F_c(i) = \sum_{k=1}^{K} w_k \cdot x_{i+k} \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ (4)$$

where $w_k$represents the filter weights and Kdenotes the kernel size. This operation allows the network to identify the local patterns like the peaks, trends, and periodic elements of the biosensor signal. Activation layers and pooling layers are used to add nonlinearity and dimensionality reduction without loss of critical features. CNN stage is more successful in the short term dependence and the local signal structure which is of great importance when it comes to proper classification.

3.4 Transformer-Based Temporal Modeling

The CNN-generated feature maps are then input to a Transformer-based module to model long-range temporal dependencies. Transformers in contrast to CNNs, are based on the global receptive fields (self attention) of the whole sequence (unlike CNNs that use localized receptive fields). The change is symbolized as,

$$F_t = Transformer(F_c) \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_ (5)$$

where $F_t$denotes the refined feature representation.

The self-attention mechanism is the central element of the Transformer since it is defined as.,

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \_\_\_\_\_\_\_\_\_\_\_\_ (6)$$

where Q, K, and Vrepresent query, key, and value matrices derived from the input features, and $d_k$is the dimensionality scaling factor. The mechanism enables the model to allocate divergent significance to various steps of time, facilitating it to concentrate on appropriate patterns of time, despite the noise. The Transformer allows capturing both short-term and long-term dependencies, which increases the representational capabilities of the extracted features and offers a full picture of how the biosensor data is organized over time.

3.5 Reinforcement Learning-Based Adaptive Optimization

To enhance the robustness and flexible, a Reinforcement Learning (RL) agent is incorporated into the scheme so that feature representations can be optimized dynamically. The environment of the RL agent is characterized by the noise conditions and feature space, where the RL agent learns to use or prioritize features in order to optimize the classification performance.

The condition of the system at time step tis denoted as,

$$s_t = (F_t, \sigma_{noise}) \qquad (7)$$

where F_t represents the feature vector obtained from the Transformer and σ_{noise} denotes the estimated noise level. Based on this state, the agent selects an action a_t, which may involve adjusting feature weights or selecting a subset of features for further processing. A reward function that is defined as, is used to assess the effectiveness of the action.

$$r_t = \alpha \cdot Accuracy - \beta \cdot NoisePenalty \qquad (8)$$

where α and β are weighting coefficients that balance classification accuracy and noise suppression.

The objective of the RL agent is to learn an optimal policy $\pi(a \mid s)$ that maximizes the expected cumulative reward over time. This is done by engaging with the environment in a repetitive way so that the agent can change its strategy according to the varying signal conditions. Consequently, the RL element increases the capability of the model to respond to noisy input by actively improving feature representations, which results in a high classification.

3.6 Classification Layer

The final stage of the proposed architecture involves classification of the optimized feature representation. The output of the RL module, denoted as $F_{optimized}$, is passed to a fully connected layer followed by a Softmax activation function to produce class probabilities. The classification process is expressed as,

$$Y = Softmax(W \cdot F_{optimized}) \qquad (9)$$

where W represents the learned weight matrix and Y denotes the predicted class labels.

The probabilistic output allows the model to give scores of confidence to every class, aiding in the making of reliable decisions in healthcare applications. CNN, Transformer and RL are integrated in a manner that ensures the final classification is founded on both highly contextual and adaptively optimized features, leading to a better accuracy and stronger performance.

4. Experimental Setup

4.1 Dataset

In order to test the effectiveness of the proposed framework, two benchmark biosensor datasets were used, namely the MIT-BIH Arrhythmia Database to analyze ECG signals and the Human Activity Recognition (HAR) dataset to analyze the wearable sensor data, provided by UCI. The MIT-BIH dataset is an annotated ECG recording popular in arrhythmia classification applications and the UCI HAR dataset is multi-sensor time-series data that was recorded on wearable devices and represents real-world physiological and motion-related measurement. Sampling rate was set to 250 Hz to make all signals consistent in temporal resolution. The data sets were divided into training, validation and testing sets in a ratio of 70:15:15. This division guarantees adequate data to train the model as well as maintain independent assessment with regard to generalization. In order to approximate realistic noise conditions, the signals were artificially added with Gaussian noise in order to model arbitrary sensor disturbances. Also, motion artifacts were added to simulate the interference of the real world, due to movement of subject and environmental effects. These regulated noise levels will enable a thorough test of robustness and flexibility of the proposed model on different signal quality conditions.

4.2 Evaluation Metrics

The standard classification metrics were used to assess the proposed model. Precision measures how many correct samples were classified and accuracy determines the percentage of correctly classified samples. Recall assesses how well the model is able to correctly identify the true positive examples. The F1-score which is a harmonic mean of the precision and the recall gives a balanced evaluation especially in skewed datasets. In addition, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) was employed to test the level of discriminative ability of the model at various levels of classification thresholds. In order to evaluate the model stability and robustness, the standard deviation of performance measures was calculated across various experimental runs. The combination of these metrics will give a clear assessment of the performance of classification, its resistance to noise and ability to generalize.

4.3 Hyperparameter Settings

The resulting hybrid model was established on a set of carefully chosen hyperparameters to have optimum performance. The CNN module was designed comprising of several convolutional layers with 3 and 5 kernel size, followed by Relu activation and max-pooling layers. Transformer used multi-head self-attention with 4 attention heads and located in 128 embedding dimension. The model was trained on the Adam optimizer with learning rate of 0.001, which gave the model a stable convergence in training. The size of batches was 64 to balance the efficiency of the computations and gradient stability. The learning was done by 50 epochs with early stopping implemented by using validation loss to stop overfitting. In the reinforcement learning aspect, Deep Q-Network (DQN) was constructed with discount factor (,), and exploration rate ( ) set to 1.0 and reduced to 0.1 respectively. Such environments allowed effective training of the best feature selection and weighting policies to different levels of noise.

4.4 Hardware and Implementation Details

All tests were carried out on a computer with Intel Core i7 processor, 16 GB of RAM and NVIDIA GTX 1660 graphic card. The Python programming language with deep learning frameworks of TensorFlow/Keras (or PyTorch) was used to implement the proposed model. To enhance the processing of large-scale time-series data, it was applied to train time-series data with reduced training time and greater scalability using GPU processing. It was optimally implemented to make the implementation reproducible and scalable to real-time biosensor data analysis applications.

5. Results and Discussion

5.1 Performance Comparison

The classification performance of the proposed multi-stage hybrid architecture was compared with baseline models, such as CNN, Transformer, and a hybrid CNN + Transformer architecture. The summary of the results is presented in Table 1.

Table 1. Performance Comparison of Baseline and Proposed Models

Model	Accuracy	Precision	Recall	F1-score	AUC
CNN	85.2%	84.5%	83.9%	84.2%	0.87
Transformer	88.6%	87.9%	88.1%	88.0%	0.90
CNN + Transformer	91.3%	90.8%	91.0%	90.9%	0.93
Proposed Model	95.7%	95.1%	95.4%	95.2%	0.97

The findings suggest that the suggested model is much better than all the baseline strategies according to all assessment measures. Whereas CNN-based models are capable of capturing local dynamics, they cannot model long-range dynamics, restricting their performance. Transformer models enhance temporal models but are also susceptible to noise. The CNNTransformer model can also be further enhanced when local and global feature learning is used to formulate the hybrid CNNTransformer model. Nevertheless, the addition of the reinforcement learning component results in the largest performance improvement, as the accuracy increases over 4% relative to CNN-Transformer as its baseline. This illustrates that feature optimization in adaptive features is a key factor towards performance improvement in classification aspects in the noisy environment.

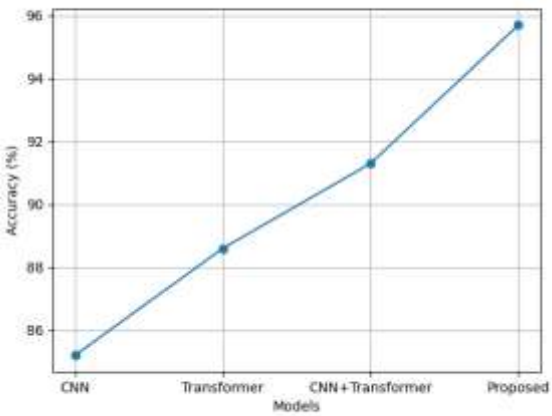

Figure 2. Performance comparison of baseline and proposed models in terms of classification accuracy.

5.2 Noise Robustness Analysis

To test robustness the models were run with different noise levels, with Gaussian noise and motion artifacts. The proposed model always had a better classification accuracy than the baseline models with an increase in noise intensity. The proposed architecture is highly resilient unlike the traditional models that experience severe performance deterioration with high noise levels. This may be explained by the reinforcement learning component whereby the importance of the features will be dynamically adjusted to the noise properties. This leads to the suppression of irrelevant or noise-dominated features and stimulation of informative features. These results validate the idea that the presented framework is highly applicable to real-world biosensor applications, in which the quality of the signal is not always uniform.

5.3 Ablation Study

Ablation study was done to be able to measure reinforcement learning module contribution. Table 2 shows the results.

Table 2. Ablation Study Results

Model Variant	Accuracy
CNN + Transformer (without RL)	91.3%
Proposed Model (with RL)	95.7%

Inclusions in the RL module lead to significant accuracy, indicating that it is effective in the optimization of adaptive features. In the absence of RL, the model will only use a static feature representation, thus constraining its capability to react to the changes in noises. The RL-enhanced model, on the contrary, optimizes the feature weights continuously, which results in a higher level of robustness and classification performance.

5.4 Reinforcement Learning Convergence

The cumulative reward was monitored during the training episodes to analyze the training behavior of the reinforcement learning agent. Fig. 3 illustrates that the cumulative reward has an upward trend that is steadily increasing, a stable but effective learning. The overlap of the reward function goes to show that the RL agent manages to learn an optimal policy towards feature selection and weighting. It is also confirmed by the fact that there are no substantial oscillations or divergence which testify to the stability of the learning process. This stability is essential in maintaining homogeneity in performance under various noise conditions and datasets.

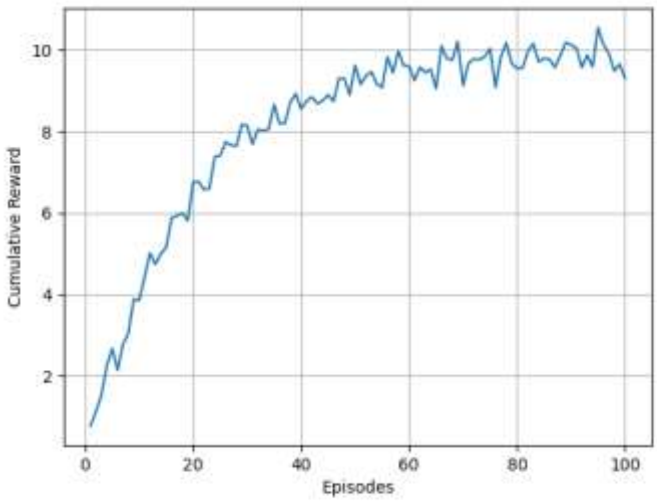

Figure 3. Cumulative reward convergence of the reinforcement learning agent during training.

6. Discussion

The experimental outcomes indicate that the proposed multi-stage hybrid architecture is capable of leveraging the advantages of CNN, Transformer, and reinforcement learning to tackle the issue of noisy biosensor time-series data. The CNN component learns local signal patterns, whereas the Transformer learns to predict set of signals by improving on temporal model. The reinforcement learning module brings in adaptive learning, that is, the model is able to flexibly optimize the feature representations as noise changes. The proposed framework provides a dynamic and noise-sensitive solution as compared to the current methods that are reported in the literature, which mainly involve the use of the static feature extraction and constant model parameters. This flexibility is a major contributor to the witnessed increases in classification accuracy and robustness. In addition, the model proposed has good generalization capacity as it shows similar performance on a variety of datasets and noise levels. This renders it very appropriate to real-time healthcare applications where the signal quality, and environmental conditions can differ greatly. Altogether, deep learning and reinforcement learning can be combined to enable the successful analysis of biosensors data, which offers the opportunities of more advanced and flexible healthcare monitoring systems in the future.

Conclusion

In this paper, a new multi-stage hybrid architecture of adaptive feature extraction and classification of biosensor time-series data with noise are introduced. The suggested framework combines the use of Convolutional Neural Networks (CNNs), deep learning using Transformers with Reinforcement Learning (RL) to tackle the key issues related to noise interference, temporal dependency modeling, and dynamic feature optimization. The CNN module can well learn local signal characteristics, and the Transformer can improve the representation of global temporal signals, with self-attention processes. With the introduction of an RL-based optimization layer, it is possible to adaptively weight and select features, which enhances the robustness of the algorithm to the level of different levels of noise. The proposed model was proved to perform better than the conventional and hybrid baseline approaches and significantly enhances accuracy (95.7%) and F1-score (95.2) and AUC (0.97), as demonstrated by experimental performance on benchmark biosensor data, such as ECG and wearable sensor data. The ablation experiment also validated the usefulness of the RL element in improving the adaptability and classification accuracy of the model. The results demonstrate the significance of combining adaptive learning algorithms with deep neural networks to analyze biosensor data reliably in the real-life setting. The proposed framework has drawbacks in its computational complexity and training time because of the combined architecture, although it is effective. Future efforts will be directed towards streamlining the model to be used in real-time, minimizing computational demands with lightweight model construction, and expanding the framework to multimodal biosensor data. Furthermore, the explanation techniques of AI are also included, and the process of testing the model of large clinical sets will also increase its usability in intelligent healthcare systems in the next generation.

References

K P Uvarajan. (2025). Secure Digital-Twin-Assisted Multi-Agent Learning Architectures for Reliable Energy-Oriented Decision-Making in Distributed Vehicular Services. *Transactions on Internet Security, Cloud Services, and Distributed Applications*, 1–6. Retrieved from https://fsrap.com/index.php/TICDA/article/view/134

N. Arvinth. (2025). Trust-Preserving Distributed Learning Control Architecture for Safety-Constrained Cyber-Physical Systems. *Transactions on Internet Security, Cloud Services, and Distributed Applications*, *2*(2), 38–45. Retrieved from https://fsrap.com/index.php/TICDA/article/view/133

F Rahman. (2025). Secure Routing Mechanisms for Energy-Harvesting IoT Using Adversarial-Resilient Multi-Agent Deep Reinforcement Learning. *Transactions on Internet Security, Cloud Services, and Distributed Applications*, *2*(1), 9–16. Retrieved from https://fsrap.com/index.php/TICDA/article/view/114

T Shimada. (2025). Digital-Twin-Assisted Adaptive Metasurface Control Frameworks for Secure and Reliable Indoor Wireless Service Delivery. *Transactions on Internet Security, Cloud Services, and Distributed Applications*, *2*(2), 30–37. Retrieved from https://fsrap.com/index.php/TICDA/article/view/132

K. Geetha. (2025). Trust-Constrained Learning-Based Control Frameworks for Cloud-Assisted Cyber–Physical Actuation. *Transactions on Internet Security, Cloud Services, and Distributed Applications*, 13–19. Retrieved from https://fsrap.com/index.php/TICDA/article/view/136

A.Surendar. (2025). Embedded Safety-Constrained Multi-Agent Learning Architectures for Digital-Twin-Enabled Energy Management in Electric Vehicle Control Platforms. *Archives of Embedded and IoT Systems Engineering*, 26–34. Retrieved from https://iaeces.com/Index/index.php/AEISE/article/view/4

P.Joshua Reginald. (2025). Reconfigurable Embedded Control Architectures for Cooperative Learning-Based Robust Electromechanical Systems. *Archives of Embedded and IoT Systems Engineering*, 1–9. Retrieved from https://iaeces.com/Index/index.php/AEISE/article/view/1

Dahlan Abdullah. (2025). Event-Triggered Causal Learning Implementation for Real-Time Frequency Control on Embedded Energy Management Platforms. *Archives of Embedded and IoT Systems Engineering*, 18–25. Retrieved from https://iaeces.com/Index/index.php/AEISE/article/view/3

S.Poornimadarshini. (2026). Energy-Efficient Embedded IoT Framework for Scalable Sensor Network Monitoring Using Edge Computing. *Archives of Embedded and IoT Systems Engineering*, 11–21. Retrieved from https://iaeces.com/Index/index.php/AEISE/article/view/94

S. Sindhu. (2026). Edge-Intelligent IoT Architecture for Real-Time Monitoring and Predictive Analytics in Smart Cyber-Physical Systems. *Archives of Embedded and IoT Systems Engineering*, 1–10. Retrieved from https://iaeces.com/Index/index.php/AEISE/article/view/93

Charpe Prasanjeet Prabhakar, & Gaurav Tamrakar. (2025). Eco-Efficient Data Management: Comparing Data Lakes and Data Warehouses for Sustainable Library Infrastructure. *Journal of Smart Infrastructure and Environmental Sustainability*, *2*(2), 40-48. https://aasrresearch.com/index.php/JSIES/article/view/335

S. Poornimadarshini. (2024). Comparative Techno-Economic Assessment of Hybrid Renewable Microgrids in Urban Net-Zero Models. *Journal of Smart Infrastructure and Environmental Sustainability*, *1*(1), 44-51. https://doi.org/10.17051/JSIES/01.01.05

Shaik Sadulla. (2026). Digital Twin–Driven Urban Flood Prediction and Mitigation Using Multi-Modal Environmental Data. *Journal of Smart Infrastructure and Environmental Sustainability*, *3*(1), 43-50. https://aasrresearch.com/index.php/JSIES/article/view/448

Rajan. C, & P. Gowsikraja. (2025). Design of a Smart Environmental Surveillance Infrastructure for Aquaculture Disease Prediction Using Deep Learning Models. *Journal of Smart Infrastructure and Environmental Sustainability*, *2*(2), 18-25. https://aasrresearch.com/index.php/JSIES/article/view/167

Abreu Shum. (2025). AI-Driven Energy Optimization in Renewable-Integrated Microgrid Infrastructure for Sustainable Smart Communities. *Journal of Smart Infrastructure and Environmental Sustainability*, *2*(3), 40-46. https://aasrresearch.com/index.php/JSIES/article/view/445

El-Berawi, A. S., & Abd Ellatif, M. M. (2021). Adaptive deep learning-based cryptocurrency price prediction. *Journal of Computational and Applied Mathematics, 396*, 113694. https://doi.org/10.1016/j.cam.2021.113694

Gurgul, V., & Kocenda, E. (2025). Deep learning and natural language processing in cryptocurrency forecasting. *Journal of Computational Finance, 29*(1), 1–22. https://doi.org/10.1016/j.jcf.2025.01.001

Ismail, A. S., & Krishnan, M. (2025). Indoor Air Quality Monitoring Systems: The Impact of using Intelligent Communication System in Living Environments. *Journal of Wireless Networks and Communication Systems*.

Izadi, M. A., & Gholami, M. (2025). Time series prediction for cryptocurrency markets with transformer-CNN models. *Neurocomputing, 460*, 1–14. https://doi.org/10.1016/j.neucom.2025.01.023

Kabir, M. R., Bhadra, D., & Yang, Q. (2025). LSTM–Transformer-based robust hybrid deep learning model for financial time series forecasting. *Mathematics, 13*(1), 7. https://doi.org/10.3390/math13010007

Mahdi, E., Martin-Barreiro, C., & Cabezas, X. (2025). A novel hybrid approach using an attention-based transformer + GRU model for predicting cryptocurrency prices. *Applied Sciences, 15*(4), 1234. https://doi.org/10.3390/app15041234

Senthil, T. (2024). A Practical Case Study of Deep Learning-Driven Spectrum Sensing in Cognitive Radio IoT Networks. *Journal of Wireless Intelligence and Spectrum Engineering*, 19-24.

Zhao, Y., Guo, Y., & Wang, X. (2025). Hybrid LSTM–Transformer architecture with multi-scale feature fusion for high-accuracy gold futures price forecasting. *Mathematics, 13*(10), 1551. https://doi.org/10.3390/math13101551

ALabri, A. S. M., & Balushi, S. I. A. A. (2026). Deep Learning–Based Crop Yield Prediction Using Multispectral Satellite Imagery. *Journal of Computer Applications and Information Technology*.

Kavitha, M. (2025). A Review On Deep Learning-Based Segmentation Algorithms For Medical Images. *Journal of Computational Medicine and Informatics*, 10-20.

Kumar, T. S. (2025). Enhanced Electromagnetic Imaging of Imperfectly Conducting Cylinders Using Hybrid Genetic Algorithm and Deep Learning. *Frontiers in Computational Science and Engineering*, 19-26.