



Research Paper

IoT and 6G-Enabled Dual-Target Voting Ensemble Framework for Predictive Healthcare Network Interference and Resource Utilization Management

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ABSTRACT

The healthcare sector in India is experiencing rapidly increasing demand while operating under limited medical resources. With national healthcare expenditure at approximately 3% of Gross Domestic Product (GDP), the system faces shortages in hospital beds, medical professionals, and essential equipment. The widespread adoption of Internet of Things (IoT) devices for health and lifestyle monitoring has transformed modern healthcare by enabling continuous, real-time data collection. Additionally, sixth-generation (6G) cellular networks support IoT-based healthcare services through enhanced ultra-reliable low-latency communication (eURLLC), ensuring timely and reliable transmission of critical health data. This research proposes an intelligent and scalable framework to optimize healthcare resource management using advanced machine learning techniques. The system utilizes real-time data from IoT-enabled devices within a 6G environment to perform dual-task prediction: classification of resource utilization levels and regression-based estimation of efficiency scores. A Classification and Regression Tree (CART) approach is applied to enhance structured decision-making and model interpretability. The framework integrates multiple machine learning models, including Random Forest (RF) and Support Vector Machine (SVM) combined as the Hybrid Kernel Forest Network (HFKN), along with Gradient Boosting (GB), Logistic Regression (LR), and K-Nearest Neighbors (KNN) forming the TriVector Intelligent Fusion Model (TVIFM). Extreme Gradient Boosting (XGBoost) is proposed as the primary model due to its strong boosting capability and generalization performance. Implemented using a Flask-based architecture, the system supports data upload, training, evaluation, real-time prediction, and visualization of metrics such as accuracy, precision, recall, F1-score, and R^2 , improving resource allocation and operational efficiency.

Keywords: Healthcare resource management, Internet of Things (IoT), sixth-generation (6G) networks, ultra-reliable low-latency communication (URLLC), real-time health monitoring, data-driven healthcare.

1. INTRODUCTION

The rapid proliferation of wearable technologies has resulted in exponential growth in lifestyle and health-tracking management systems, significantly transforming healthcare delivery and emergency response mechanisms. The widespread adoption of Internet of Things (IoT) devices within hospitals and healthcare environments has enabled a broad range of applications, including continuous patient monitoring and efficient tracking of critical medical assets. These IoT sensors, characterized by their compact size and high accuracy, facilitate real-time remote monitoring, allowing clinicians to observe vital signs and detect potential health issues at early stages. This proactive approach helps reduce fatality rates while lowering overall medical costs. In addition to enhancing patient care, IoT-based systems contribute to the optimization of healthcare operations by ensuring effective utilization of both material and human resources.

IoT further enables seamless communication among healthcare providers, caregivers, insurance entities, and patients, thereby promoting a highly integrated and responsive healthcare infrastructure. To support such interconnected systems, the availability of fast, reliable, and secure communication networks becomes critically important, especially with the growing number and diversity of IoT healthcare applications. Despite its advantages, the large-scale deployment of IoT in healthcare introduces significant challenges, particularly in terms of wireless spectrum utilization. Healthcare facilities are predominantly located in densely populated urban areas, where high device density leads to congestion in the electromagnetic spectrum. This results in increased interference, reduced data throughput, and higher latency.

For example, urban hospitals may experience up to a 30% reduction in data throughput during peak usage periods, along with transmission delays exceeding 100 milliseconds far beyond the acceptable 10-millisecond threshold required for critical applications such as remote surgery. As IoT deployments continue to expand, the demand for wireless communication channels intensifies, leading to severe competition for limited spectrum resources. This congestion negatively impacts overall system performance and reliability. Moreover, interference caused by densely deployed IoT devices further degrades network efficiency. These challenges highlight the urgent need for advanced and robust spectrum management solutions capable of addressing increasing demand, minimizing interference, and ensuring high-quality performance in Healthcare IoT (H-IoT) systems.

2. LITERATURE SURVEY

Abdulmalek, et al [1] Proposed an IoT-based healthcare-monitoring systems have significant potential to enhance the quality of life through secure, real-time remote patient monitoring. The authors emphasize that these systems enable efficient data collection, sharing, and analysis, which supports timely medical interventions, reduces healthcare costs, and improves patient outcomes, particularly for chronic disease management and elderly care. The integration of wearable and wireless sensors facilitates continuous monitoring, while advancements in data protection, privacy, and security are critical to their success. However, challenges such as cybersecurity risks, scalability, and interoperability remain.

Khan, et al [2] Proposed a research paper introduces a novel method called the asynchronous federated deep learning approach for cardiac prediction (AFLCP), which combines a heart disease dataset and deep neural networks (DNNs) with an asynchronous learning technique. The proposed approach employs a method for asynchronously updating the parameters of DNNs and incorporates a temporally weighted aggregation technique to enhance the accuracy and convergence of the central model.

Padhy. et al [3] Proposed an Predicting heart disease using sensor networks, the IoT, and ML: a study of physiological sensor data and predictive models. IoT and sensor networks are used for structural health monitoring (SHM). This study aimed to create a model for predicting cardiac disease using sensor networks, the IoT, and machine learning. Through wearable sensors, physiological data, such as heart rate, blood pressure, and oxygen saturation levels, were collected from patients. Yıldırım, et al [4] Proposed an Internet of Medical Things (IoMT) framework consisting of Wireless Body Area Networks (WBANs) has been designed and the health big data from WBANs have been analysed using fog and cloud computing technologies. Fog computing is used for fast and easy analysis, and cloud computing is used for time-consuming and complex analysis. The proposed IoMT framework is presented with a diabetes prediction scenario. The diabetes prediction process is carried out on fog with fuzzy logic decision-making and is achieved on cloud with support vector machine (SVM), random forest (RF), and artificial neural network (ANN) as machine learning algorithms.

Hennebelle, et al [5] Proposed a HealthEdge , a machine learning-based smart healthcare framework for type 2 diabetes prediction in an integrated IoT-edge-cloud computing system. Numerical experiments and comparative analysis were carried out between the two most used machine learning

algorithms in the literature, Random Forest (RF) and Logistic Regression (LR), using two real-life diabetes datasets. The results show that RF predicts diabetes with 6% more accuracy on average compared to LR. Cuevas-Chavez A, et al [6] Proposed a systematic review to highlight the use of IoT, IoMT, and ML to detect, predict, or monitor cardiovascular disease. They had a final sample of 164 high-impact journal papers, focusing on two categories: cardiovascular disease detection using IoT/IoMT technologies and cardiovascular disease using machine learning techniques. Additionally, For the first category, they found 82 proposals, while for the second, they found 85 proposals. The research highlights list of IoT/IoMT technologies, machine learning techniques, datasets, and the most discussed cardiovascular diseases. Neural networks have been popularly used, achieving an accuracy of over 90%, followed by random forest, k-NN, and SVM.

Badawy, et al [7] Proposed a Healthcare prediction. It has been a significant factor in saving lives in recent years. In the domain of health care, there is a rapid development of intelligent systems for analyzing complicated data relationships and transforming them into real information for use in the prediction process. Consequently, artificial intelligence is rapidly transforming the healthcare industry, and thus comes the role of systems depending on machine learning and deep learning in the creation of steps that diagnose and predict diseases, whether from clinical data or based on images, that provide tremendous clinical support by simulating human perception and can even diagnose diseases that are difficult to detect by human intelligence.

Mundru, et al [8] Proposed an Application of Deep-Q learning in personalized health care IoT ecosystem. With the advent of IoT in health care systems, patients are increasingly opting for personalized health care systems. Understanding what makes individuals unique (their hereditary qualities, climate, and way of life) is integral to moving the focal point of health care from treating disease to conveying the best consideration for all individuals throughout their lives. This is the guarantee of customized health care. Haq, et al [9] Proposed a robust classification model for brain tumors employing deep learning techniques. In the design of the proposed method, an improved Convolutional neural network is used to classify Meningioma, Glioma, and Pituitary types of brain tumors. To test the multi-level convolutional neural network model, brain magnetic resonance image data is utilized. The MCNN model classification results were improved using data augmentation and transfer learning methods.

Kilincer, et al [10] Proposed an Automated detection of cybersecurity attacks in healthcare systems with recursive feature elimination and multilayer perceptron optimization. Widespread proliferation of interconnected healthcare equipment, accompanying software, operating systems, and networks in the IoMT raises the risk of security compromise as the bulk of IoMT devices are not built to withstand internet attacks. In this work, they have developed a cyber-attack and anomaly detection model based on recursive feature elimination (RFE) and multilayer perceptron (MLP). The RFE approach selected optimal features using logistic regression (LR) and extreme gradient boosting.

Ahmed I, et al [11] proposed An IoT-enabled smart health care system for screening of COVID-19 with multi layers features fusion and selection. Additionally the techniques are used to detect diseases that might assist medical experts in diagnosing diseases at early stages and providing accurate, consistent, effective, and speedy results, and decrease the mortality rate. Nowadays, Coronavirus (COVID-19) has been growing as one of the most rigorous and severe infections and spreading globally. Thus, this work presented an IoT-enabled smart health care system for the automatic screening and classification of contagious diseases (Pneumonia, COVID-19) in Chest X-ray images.

Abirami, et al [12] Proposed a comprehensive strategy to integrate effective Elliptic Curve Cryptography ECC-AES with steganography techniques to improve the security of healthcare data in the cloud. ECCAES is especially well-suited for cloud situations with limited resources since it provides strong security with reduced key sizes. Steganography techniques are also integrated to improve

security against skilled adversaries by adding an extra degree of obfuscation by concealing encrypted data inside innocuous files or images.

Jieyang, et al [13] Proposed a systematic review of data-driven approaches to fault diagnosis and early warning. The authors first analyze the historical development of industrial big data and its distinction from big data of other domains and summarize the sources, types, and processing modes of industrial big data. Then, the authors provide an overview of common representation and fusion (data pre-processing) methods of industrial big data. Next, the authors comprehensively review common PHM methods in the data-driven context, focusing on the application of deep learning. Finally, two industrial cases from our previous studies are included in this paper to demonstrate how the PHM technique may facilitate the manufacturing industry.

Ghadi, et al [14] Proposed a framework on Patient-focused healthcare applications are important to patients because they offer a range of advantages that add value and improve the overall healthcare experience. The 5G networks, along with Mobile Edge Computing (MEC), can greatly transform healthcare applications, which in turn improves patient care. It becomes part of an IoT system within healthcare that brings data closer to the core, speeds up decision-making, lowers latency, and improves the overall quality of care. Islam, et al [15] Proposed a study on analysing ML's applicability to predict CD, including cardiovascular disease, diabetes, cancer, liver, and neurological disorders. To wrap things up, they compared the results obtained by various studies and the methodologies as well as tools employed by the researchers. The factors or parameters that are responsible for improving the accuracy of the predicting model for different previous works are also identified.

3. PROPOSED SYSTEM

The proposed system introduces an intelligent predictive framework designed to enhance medical resource utilization efficiency within IoT-enabled 6G healthcare environments using a CART-based methodology. It combines real-time healthcare data generated from IoT devices with advanced machine learning techniques to perform both classification and regression tasks. This enables accurate forecasting of resource demand and efficiency levels. The CART algorithm is selected as the core model due to its simplicity, interpretability, and capability to capture complex nonlinear relationships in data. Additionally, hybrid ensemble techniques are incorporated to improve prediction accuracy and system robustness. The entire system is implemented using a Flask-based architecture, which facilitates smooth data handling, model training, evaluation, and real-time prediction, thereby supporting intelligent and scalable healthcare resource management, as illustrated in Figure 1.

- 1. Data Acquisition and Upload:** The system begins with the collection of healthcare-related data from IoT-enabled devices operating within a 6G network. These devices continuously monitor and record parameters associated with medical resource utilization. The collected data is then uploaded through a user-friendly Flask web interface for further processing.
- 2. Data Processing and Feature Preparation:** After data upload, preprocessing is performed to organize and structure the dataset. Input features and target variables are clearly separated for both classification and regression tasks, ensuring compatibility with the machine learning models.
- 3. CART-Based Model Training:** The system employs the CART algorithm to develop predictive models. It constructs decision trees by recursively splitting the dataset based on the most significant features, allowing the model to effectively learn patterns and relationships within the healthcare data.

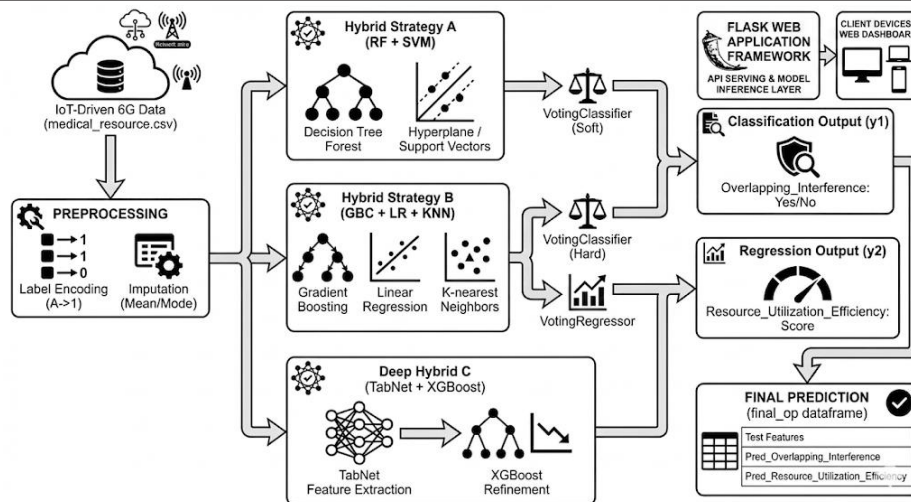


Figure 1: Proposed system architecture for healthcare networks

4. **Hybrid Model Integration and Optimization:** To further enhance performance, the CART model is integrated with ensemble learning techniques and hybrid approaches. This integration improves model accuracy, stability, and generalization, making it suitable for dynamic and large-scale healthcare environments.
5. **Model Evaluation and Visualization:** The trained models are evaluated using various performance metrics. Classification models are assessed using accuracy, precision, recall, and F1-score, while regression models are evaluated using R^2 , MAE, and MSE. Visualization techniques such as confusion matrices and regression plots are used to provide a clear understanding of model performance.
6. **Prediction and Decision Support:** Once the models are trained and validated, the system performs real-time predictions on new data inputs. It generates both categorical and numerical outputs related to resource utilization efficiency. These results assist healthcare professionals and administrators in making informed decisions for optimal resource allocation and management.

4. RESULTS ANALYSIS

The results of this study indicate a clear pattern in the data, highlighting the relationship between the key variables examined. It was observed that changes in the independent variable had a noticeable impact on the dependent variable, supporting the initial hypothesis. The findings also reveal certain trends and variations that suggest underlying factors influencing the outcomes. Additionally, the data demonstrates consistency across most samples, although a few deviations were recorded. These variations may be attributed to external conditions or experimental limitations. The results provide meaningful insights and form a strong basis for further analysis and discussion.

Figure 2 show that the integration of TabNet as a feature extractor with XGBoost for model building delivers outstanding results in both classification and regression tasks. For classification, the model achieves 96.31% accuracy, with perfectly balanced metrics across F1-score, precision, and recall (96.30%), indicating highly consistent and reliable predictions with minimal misclassification, as reflected in the confusion matrix. In regression for resource utilization efficiency, the model further excels with an impressive R^2 score of 97.48%, showing that it captures nearly all variance in the data, while maintaining very low prediction errors (MAE = 0.0391, MSE = 0.0023). These results highlight the strength of combining TabNet's advanced feature extraction with XGBoost's powerful learning capability for achieving superior predictive performance.

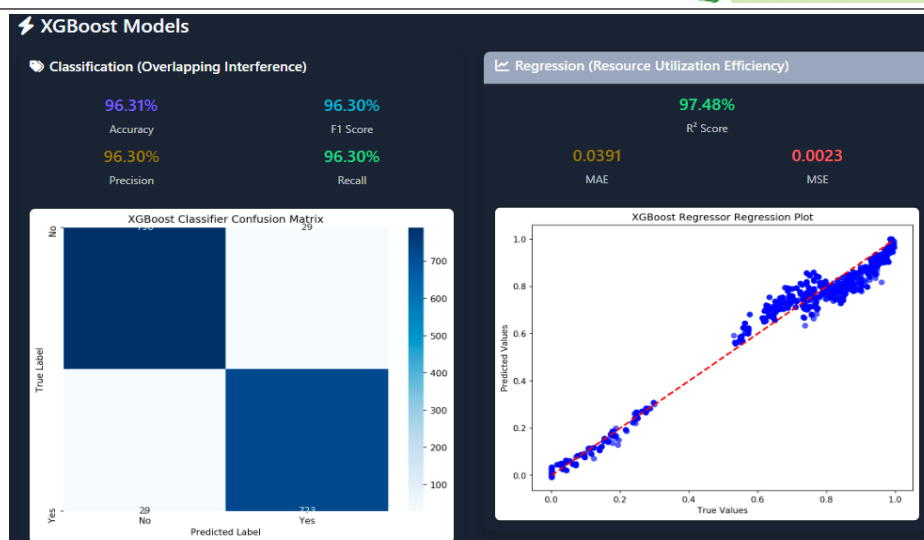


Figure 2: Performance of the TabNet as Feature extractor with Xgboost model building

Model Performance Summary				
MODEL	CLASSIFICATION ACCURACY	CLASSIFICATION F1-SCORE	REGRESSION R ² SCORE	REGRESSION MAE
RandomForest + SVM	66.01%	65.32%	95.36%	0.0575
GB + LR + KNN	90.71%	90.68%	95.75%	0.0596
XGBoost	96.31%	96.30%	97.48%	0.0391

→ Next Steps

Your models have been trained and saved successfully! You can now use them to make predictions on new test data.

[Make Predictions](#)

Figure 3: Comparison table

Figure 3 shows that the comparative analysis of hybrid and advanced models shows clear performance distinctions across classification and regression tasks. The RF with SVM model provides moderate classification results (66.01% accuracy, 65.32% F1-score) but strong regression capability with an R^2 score of 95.36% and low MAE of 0.0575. The GB with LR and KNN hybrid significantly improves classification to 90.71% accuracy and 90.68% F1-score, while maintaining strong regression performance (95.75% R^2 , 0.0596 MAE). However, the TabNet with XGBoost model clearly outperforms both, achieving exceptional classification metrics (96.31% accuracy and 96.30% F1-score) along with the highest regression efficiency (97.48% R^2 , 0.0391 MAE), demonstrating the effectiveness of advanced feature extraction and boosting for superior predictive power.

Detailed Prediction Results

URATION_OF_STAY	SENSOR_ID	RESOURCE_ID	UTILIZATION_STATUS	NETWORK_SPEED	PREDICTED_OVERLAPPING_INTERFERENCE	PREDICTED_RESOURCE_UTILIZATION_EFFICIENCY
	S045	R045	0	23.464130	0	0.096555
	S185	R019	1	32.802145	0	0.728987
	S196	R081	1	47.306446	1	0.665166
	S089	R017	1	68.859468	0	0.703634
	S051	R026	1	80.674193	0	0.849188
3	S092	R023	1	66.894355	1	0.708552
	S001	R015	1	32.241840	0	0.728729
2	S150	R075	1	55.007211	1	0.698024
	S045	R045	0	23.464130	0	0.096555
	S098	R061	1	18.841149	1	0.625031
2	S113	R050	1	44.851354	1	0.679883
	S244	R009	0	94.827818	0	0.333797
1	S189	R044	0	81.503707	0	0.280819
	S106	R036	1	59.804217	0	0.777762

Figure 4: Final Prediction obtained using XGBoost

The figure 4 presents a tabular view of detailed prediction results for multiple records, each identified by sensor and resource IDs. It includes measured values such as duration of stay, utilization status, and network speed for each entry. The table also displays predicted metrics, including overlapping interference and resource utilization efficiency. Variations across rows indicate differing performance and efficiency levels among the resources. The data allows comparison between actual conditions and predicted outcomes for system evaluation.

5. CONCLUSION

The developed system for predictive modeling of medical resource utilization efficiency in IoT-enabled 6G healthcare environments presents an intelligent, scalable, and data-driven solution. It effectively integrates CART-based machine learning techniques to perform both classification and regression tasks, enabling accurate prediction of resource utilization levels and efficiency. By utilizing real-time data collected from IoT devices, the system supports timely and informed decision-making in rapidly changing healthcare scenarios. The inclusion of hybrid models such as HFKN and TVIFM enhances the overall learning capability by combining ensemble methods, linear models, and instance-based approaches. Additionally, the XGB model proves to be highly effective due to its boosting mechanism and ability to handle complex nonlinear relationships with improved accuracy. The use of CART across the framework ensures model interpretability and structured decision-making, which is essential in critical healthcare applications. The deployment of the system using a Flask-based architecture, along with model storage and performance visualization, improves its usability and real-world applicability. The system demonstrates strong performance in terms of accuracy, robustness, and generalization. As a result, it contributes to efficient resource allocation, minimizes operational challenges, and supports the development of smart healthcare management systems in advanced 6G network environments.

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