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Research Article

Smart Health Informatics Platform for Predictive Diagnosis and Resource Optimization in Rural U.S. Communities

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ABSTRACT

This study presents a smart predictive healthcare framework tailored to support individuals in the United States living with chronic conditions, especially those receiving care at home. The framework incorporates a deep learning model that analyzes large volumes of patient data, including vital signs, physical activity, medication usage, and symptoms. These data are collected through ambient assisted living technologies. The model is part of an intelligent module that operates at the patient's location to deliver accurate health status predictions and personalized care recommendations. The framework was tested using data from patients with chronic blood pressure conditions, collected every 15 minutes over one year. The proposed model achieved a prediction accuracy of approximately 97.6% % outperforming a standard baseline model by nearly 6%. Additionally, improvements in identifying critical health events were observed, with the F score increasing by 9% for hypertensive, 26% for hypotensive, and 10% for normotensive cases. These results demonstrate the model's effectiveness in detecting early warning signs and enhancing the management of chronic diseases. The framework shows strong potential for improving healthcare access and reducing emergency risks in rural and underserved communities across the United States.

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1. Introduction

In the United States, chronic diseases such as cardiovascular conditions, diabetes, respiratory disorders, and various forms of cancer are among the primary causes of death and long-term disability. According to the Centers for Disease Control and Prevention, six in ten adults in the U.S. live with at least one chronic disease, and four in ten have two or more (Organization, 2019). These conditions are responsible for nearly 90 percent of the country's healthcare expenditures. Globally, similar patterns are observed. The World Health Organization reported that by 2020, chronic illnesses accounted for approximately 80 percent of all deaths, a notable increase from 71 percent in 2000 (Organization, 2003). This trend is largely driven by longer life expectancy and an aging population, both of which are significant factors in the American healthcare landscape.

The rise in life expectancy comes with an increased demand for long-term care. However, a shortage of healthcare professionals and caregivers, especially in rural regions, combined with the high cost of treatment, continues to put pressure on the system (Hassan et al., 2018). These challenges underline the need for intelligent healthcare solutions that can support early diagnosis, reduce emergency hospital visits, and ensure cost-effective care for chronic disease management. Among the most promising innovations are smart predictive healthcare frameworks that combine artificial intelligence, deep learning, and big data analytics to deliver timely, actionable insights from continuous health monitoring.

To support individuals living with chronic conditions, particularly those receiving care at home, researchers are developing intelligent frameworks that integrate data from multiple sources. These include wearable devices, environmental sensors, medication logs, and health records. In the U.S., especially in remote or underserved areas where regular access to hospitals is limited, these technologies are proving essential (Hämäläinen & Li, 2017; SL, 2019). Such systems form part of what is known as Ambient Assisted Living environments, where patient data is continuously collected and transmitted for monitoring and analysis. These data streams contain valuable information about a person's daily activity, vital signs, medication intake, and symptoms (Negra et al.,

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2016). To analyze this complex and dynamic information, robust computational models are required.

Big data analytics, supported by deep learning techniques, allows for the detection of subtle patterns and shifts in patient health status (Normandeau, 2013). Unlike traditional statistical methods, deep learning models can manage highly variable and incomplete datasets and identify correlations that may be overlooked by human practitioners (Gope & Hwang, 2015). These models can classify patient health states into multiple categories, such as normal, alert, warning, and emergency. This multi-class approach is far more effective than earlier binary classification systems that simply indicate the presence or absence of a disease (Mahdavinejad et al., 2018).

However, most existing predictive models have limitations. Many have been developed and tested in narrow clinical settings, limiting their generalizability to diverse populations. Others are not well suited for continuous real-time use or fail during data interruptions, especially in rural environments where internet connectivity is unreliable (Rathore et al., 2016). Cloud-based architectures, while offering scalable solutions, may leave patients vulnerable during service outages (Sun et al., 2018). Therefore, a new approach is needed—one that is context-aware, adaptive, and capable of operating even under limited connectivity.

This study introduces a smart predictive healthcare framework designed specifically for application in the United States, with a focus on rural and remote communities. The framework is built around a deep learning model that processes real-time data locally, reducing dependence on cloud services (Maheswar et al., 2019). It can operate as an edge computing system, analyzing data within the patient's environment. This allows for quick decision-making and the generation of timely alerts, even if internet access is unavailable. The model incorporates contextual information, such as the patient’s lifestyle and medical history, to deliver more personalized recommendations and diagnoses.

The framework also features optimized cost-performance measures. It is designed to be scalable, meaning it can accommodate large patient populations, and robust enough to continue functioning despite sensor errors or partial data loss. It can adapt over time by learning from new patient data and refining its predictions accordingly (Collins et al., 2013). In this way, it supports continuous care and adjusts to changes in patient health status.

Several key technologies converge in this framework, including mobile communication, wireless sensor networks, the Internet of Things, and wearable computing. Together, they create a seamless healthcare monitoring system capable of collecting, transmitting, and analyzing vast amounts of data. These technologies align with national initiatives in the U.S., such as the Department of Health and Human Services’ promotion of digital health innovation to improve access and equity in healthcare delivery (Levander & others, 2024).

Artificial intelligence, particularly deep learning, enhances the capabilities of these systems by enabling predictive modeling. Health conditions like high blood pressure, heart disease, and diabetes often develop gradually, with subtle warning signs that can be easily missed (Adekunle et al., 2021). By analyzing patterns in data over time, AI can forecast the likelihood of a patient entering a critical state, allowing preventive measures to be taken in advance. This not only improves individual health outcomes but also reduces the financial and logistical burden on hospitals and emergency services.

In addition to direct patient monitoring, the framework also supports clinicians. It provides them with dashboards and alerts that can assist in decision-making and patient prioritization. Predictive analytics helps providers identify patients who are at the highest risk, enabling early interventions that can prevent complications. Over time, the model becomes more accurate as it learns from both patient data and clinical outcomes. This continuous feedback loop ensures that the system evolves and improves its predictive power (Kibria et al., 2018).

While many earlier models focus primarily on diagnosing disease, the proposed framework takes a more holistic view by also assessing patient behavior, environmental factors, and lifestyle choices. This approach is consistent with modern public health strategies that emphasize preventive care and social determinants of health. It is particularly relevant in American rural settings where healthcare resources are limited and patient education and self-management play a central role in chronic disease control (Smith & others, 2017).

Looking ahead, this framework could be expanded to monitor other conditions such as chronic obstructive pulmonary disease, arthritis, or neurodegenerative disorders (Iqbal et al., 2024). Future iterations may also incorporate genomic data, behavioral assessments, and integration with national electronic health record systems, enhancing personalization and precision in care delivery. To ensure real-world applicability, additional clinical trials and validations using diverse patient data from various U.S. regions will be important. Data privacy, system interoperability, and compliance with federal regulations such as HIPAA will also be essential components of successful implementation (Balogun, 2025).

In conclusion, smart predictive healthcare frameworks built on deep learning models offer a promising pathway toward more responsive, efficient, and personalized chronic disease management in the United States. By enabling real-time monitoring and early diagnosis, these systems reduce the strain on healthcare infrastructure, particularly in rural and underserved communities. As healthcare continues to evolve, adopting such intelligent and adaptive technologies will be vital for improving population health outcomes and achieving long-term sustainability.

2. Methods

Deep learning models are widely used in healthcare for tasks such as classification and regression, depending on the specific medical prediction challenge (Koshimizu et al., 2020). The effectiveness of these models heavily depends on the choice of a cost or loss function that aligns with the problem at hand. In multiclass classification, such as identifying different stages of a patient’s health condition, Categorical Cross Entropy (CCE) is commonly used due to its suitability for evaluating classification performance. In this research, a predictive deep learning model is developed with an optimized cost function based on an enhanced version of CCE. The model is tuned using an adaptive learning rate approach, specifically tailored to categorize patient health status into four classes: emergency, alert, warning, and normal. This model is particularly designed to function effectively in the U.S. healthcare context, with a focus on supporting remote and rural patient care through intelligent edge-based systems.

2.1 Synthetic Data Generation

In real-world U.S. healthcare settings, there is often a lack of long-term patient monitoring datasets—especially for chronic conditions like blood pressure disorders—collected through IoT-enabled devices (see Table 1) (Motwani et al., 2021). To address this gap, a synthetic dataset was generated for this study. The dataset mimics real-time health monitoring using data derived from three actual patients over a one-year period sourced from the PhysioNet MIMIC-II database (Saeed & others, 2011). This data was augmented and simulated using MySignals e-Medical IoT kits, which are compatible with open-source U.S. health platforms and widely used in telehealth applications. The synthetic dataset includes vital sign readings (such as blood pressure, heart rate, and respiratory rate), ambient room conditions like temperature and humidity, and patient activity data, sampled every 15 minutes (Alam & others, 2016). These values were contextualized and labeled according to standard U.S. medical protocols for response actions, ensuring realistic simulation and classification of patient states. Previous studies have validated that synthetic biomedical data generated in this manner is highly effective in replicating real patient monitoring over extended periods, particularly for training predictive models in chronic disease management.

Table 1. Data set sample

Time stamp	01-01-2018 00:00	07-04-2018 22:30	07-12-2018 03:45	01-01-2019 04:15
Heart rate (HR)	67	98	106	179
Systolic BP (SBP)	110	127	163	53
Diastolic BP (DBP)	75	88	117	106
Respiratory rate (RR)	15	7	14	20
Oxygen saturation (SpO2)	97	92	91	65
Activity (Act)	6	2	3	3
Last-activity (L_Act)	5	6	3	4
Ambient condition (Amb)	0	1	0	2
Medication (Med)	0	1	0	1
Symptoms (Symp)	0	26	8	55
Class	1	2	3	4

2.2 Framework Description

The architectural framework developed in this study consists of three layers designed to function seamlessly within home-care or remote monitoring setups in the United States (see Figure 1). The first layer, known as the Ambient Assisted Living (AAL) layer, is responsible for monitoring and capturing the patient's vital signs and surrounding environmental data (Gupta et al., 2025). This includes body temperature, heart rate, blood pressure, room temperature, and humidity levels. It is supported by the MySignals platform, which provides flexible connectivity and integration with a wide range of medical sensors (Saif et al., 2022). These systems are increasingly used in U.S. telehealth initiatives to extend care to aging populations, especially in under-resourced communities.

The second layer, called the Local Intelligent Module (LIM), functions at the edge of the network using edge devices such as IoT gateways and local storage units (Xu & others, 2021). This layer collects, stores, and processes the data received from the AAL layer in both online and offline modes. It is particularly vital for maintaining continuity of care when internet connectivity is unreliable—a common issue in rural parts of the U.S. The LIM includes the proposed deep learning model, which performs real-time classification and prediction of patient health conditions. It also executes immediate actions such as alerting medical professionals or assistive caregivers when critical conditions are detected.

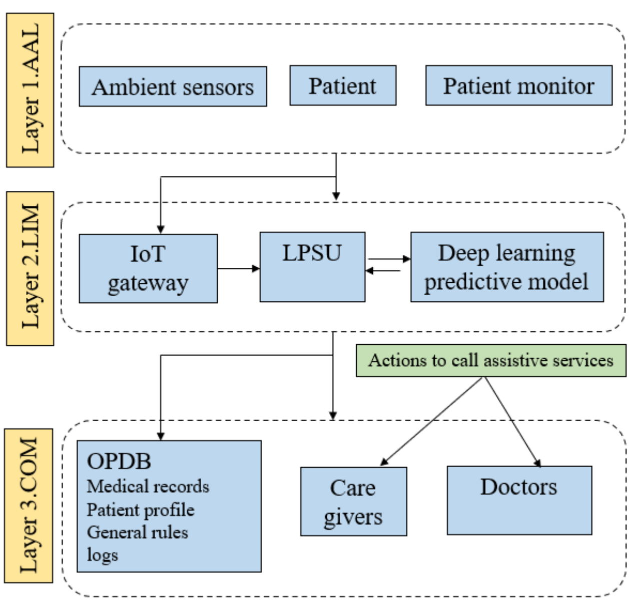

Figure 1. A smart predictive healthcare framework for remote patient monitoring

The third layer, termed the Cloud-Oriented Module (COM), serves as a centralized knowledge base (Miklošík & Hvizdová, 2012). It stores personalized patient information, medical histories, clinical rules, and other decision-support resources. It is composed of one or more secure cloud environments and synchronizes continuously with the LIM. Medical experts, caregivers, and assistive services access this layer to review patient updates, provide recommendations, and initiate remote care actions. In a typical U.S. deployment, this layer would comply with federal data privacy laws, including HIPAA, and integrate with electronic health record systems.

2.3 Proposed Predictive Model

The deep learning model introduced in this work operates within the LIM and differs from prior models that function solely on the cloud (see Figure 2). It is designed to perform local predictions using real-time data collected from the patient's surrounding environment and physiological sensors. This design ensures that even if internet service is disrupted or cloud access is delayed, the system can still function effectively by using the latest locally stored data. This approach is essential for ensuring consistent healthcare in remote areas across the United States, where network availability can vary significantly.

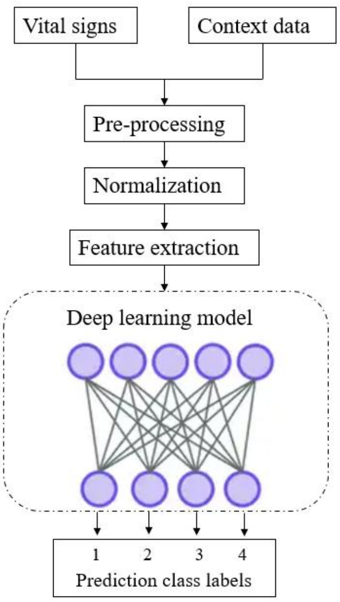

Figure 2. Predictive model with novel Categorical Cross Entropy loss function for classification of BP disorder

The input to the model includes vital signs and AAL-generated data. Prior to feeding data into the model, it undergoes preprocessing and normalization using z-score techniques to ensure uniformity. Feature engineering is then applied to derive relevant indicators based on the patient's activity patterns and environmental context. The deep learning model itself is composed of five layers with node configurations as follows: 12 nodes in the input layer, followed by 24, 12, and 6 nodes in the hidden layers, and 4 nodes in the output layer corresponding to the four health states. The model training follows the function:

$$Z = \sum_{i=1}^{m} W_i^h X_i + b$$

where W^h represents the weights for layer h, and X denotes the input features for each data point. Once the probability scores are calculated, they are processed through a novel cost optimization function before being finalized using a softmax activation function, which helps in accurate classification.

2.4 New Cost Function

Training deep neural networks effectively requires a well-constructed cost function that measures the difference between the predicted and actual outcomes (Qi et al., 2019). Poor cost function choices can lead to model instability, inaccurate predictions, or non-converging training processes. To improve learning efficiency and output precision, a new cost function based on the Categorical Cross Entropy (CCE) method has been developed.

In traditional CCE, all errors are treated equally. However, this model introduces an adaptive approach that adjusts the loss dynamically based on the variability in prediction accuracy. If the individual prediction error for a data point, denoted E(W), exceeds the average error across the dataset, a refined adjustment is applied using the following formulation:

$$z_i = [y_i \log(\hat{y}) - E(W)] \ \ if \ y_i \log(\hat{y}) > E(W)$$

$$E(W) = -\sum_{i=1}^{k} z_i$$

Here, y_i refers to the true label probability and y is the predicted probability. This modification helps to better penalize larger misclassifications while stabilizing the gradient updates, allowing for more precise convergence. The Adam optimizer is used for training, which dynamically adjusts learning rates for each parameter. This adaptive behavior supports rapid convergence even with small learning rates, which is particularly valuable in real-time patient monitoring scenarios.

This improved loss function ensures better gradient flow during backpropagation and leads to faster, more stable training of the model. A comparison between the new cost function and standard CCE, as shown in Figure 3 of the original study, illustrates how the proposed function leads to lower loss values and more accurate probability distributions.

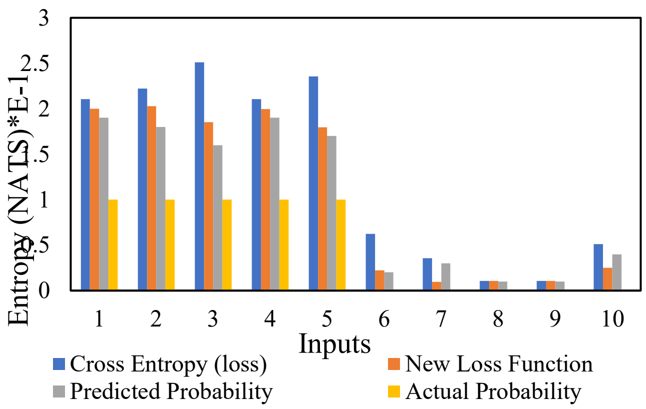

Figure 3. Comparison of cross entropy loss and novel loss function

Overall, the predictive model used in this research demonstrates improved classification performance under varied healthcare conditions, such as emergency or warning states. It provides reliable and timely insights into patient health status, even when operating independently at the edge. This is particularly useful in rural or underserved regions of the U.S., where constant connectivity cannot be guaranteed, yet timely medical decisions are crucial. The intelligent integration of this cost-optimized deep learning model with local and cloud-based systems ensures comprehensive chronic disease management and responsive care delivery across diverse healthcare environments.

3. Experiments

To evaluate the effectiveness of the proposed predictive deep learning model and the novel cost optimization function, a series of experiments were conducted. The primary objective of these experiments was to assess how accurately the model could classify and predict the actual health status of patients in real-time, enabling the system to generate timely alerts for caregivers, connect with the patient's social support network, and initiate assistive services when needed.

The experiments focused on processing an imbalanced dataset, which reflects the real-world distribution of various patient conditions. The number of instances corresponding to each health class—emergency, warning, alert, and normal—was recorded for different types of patients and is presented in Table 2. This distribution was carefully considered to ensure the model's robustness across different patient profiles.

Table 2. Class distribution for patient data

Patient type	Emergency	Alert	Warning	Normal
Hypertensive (P1)	175	2404	23347	9307
Hypotensive (P2)	148	1627	14003	19455
Normotensive (P3)	109	1186	21421	12517

For model training and evaluation, the dataset was split into training and testing subsets, with 70 percent used for training and the remaining 30 percent for testing. This split helped simulate a practical deployment scenario and provided sufficient data for both learning and performance validation.

The experiments were executed on a standard computing setup equipped with an Intel Core i3 processor (5th Generation), 8 GB of RAM, and a 4-core architecture, running on a 64-bit Windows 10 operating system. To implement and test the model, widely used and compatible machine learning and deep learning libraries were utilized, including Scikit-learn, Keras, and Google TensorFlow. These tools supported the model development, mathematical computations, and visualization tasks essential for analyzing results.

4. Results and Discussions

To assess whether the proposed predictive deep learning model can deliver reliable recommendations for remotely monitored patients, its performance was compared against two established models: a standard neural network and the Naive Bayes classifier used in the IHCAM-PUSH system. The evaluation was conducted across three types of patients with varying health profiles to ensure the robustness of the model.

Several standard metrics were used to evaluate and compare model performance. These included classification accuracy, precision, sensitivity (also known as recall), and the F-score. Classification accuracy measures the overall correctness of the model's predictions and is commonly used as a baseline metric. As shown in Figure 4, the proposed model outperforms the benchmark models in terms of classification accuracy across all patient categories. Precision reflects the proportion of true positive predictions among all predicted positives, while sensitivity indicates the proportion of actual positive cases correctly identified by the model. The F-score, a weighted average of precision and recall, provides a more balanced view of the model's performance, especially in imbalanced datasets.

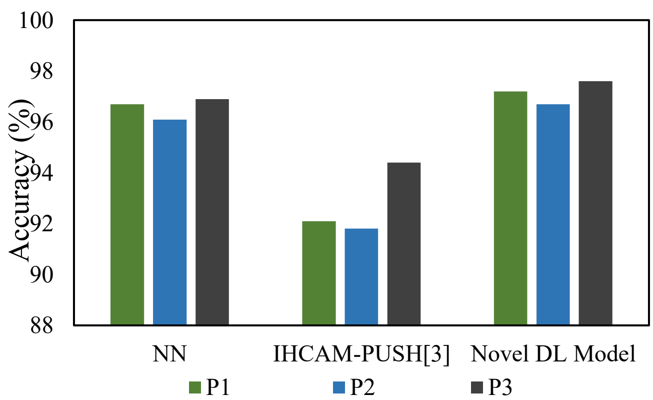

Figure 4. Comparison of accuracy for patient P1, P2, and P3

Figure 5 for both the average F-score and the F-score specific to emergency cases for all three models. The proposed model consistently achieves higher F-scores, with an average of approximately 0.92 across patient types and an emergency-class F-score exceeding 0.90. These values indicate a strong ability to detect critical conditions, even in the presence of significant class imbalance.

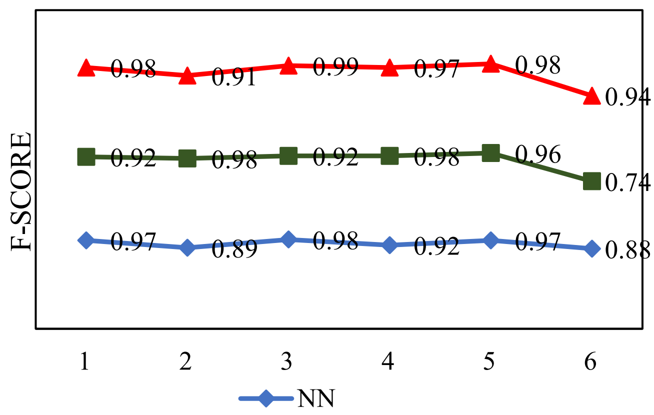

Figure 5. Comparison of F-score values

As reported in Table 3, the predictive model achieved an overall accuracy of approximately 97.6 percent, outperforming the comparison models. The results demonstrate that the model not only identifies normal and non-critical conditions with high accuracy but also excels in predicting emergency and warning states, which are essential for timely intervention. Overall, the findings confirm that the proposed model provides a dependable and accurate classification of patient health status, making it well-suited for deployment in remote monitoring scenarios within U.S. healthcare settings.

Table 3. Comparison of precision (emergency) and recall (emergency) of novel DL (proposed) model with benchmark neural network (NN)

Model	P1 Precision	P1 Recall	P2 Precision	P2 Recall	P3 Precision	P3 Recall
NN	1.00	0.80	1.00	0.86	1.00	0.79
Novel DL Model	1.00	0.83	1.00	0.84	1.00	0.89

5. Conclusions and Future Recommendation

The healthcare monitoring framework proposed in this study is designed to support the real-time supervision of patients in the United States who are living with chronic conditions such as blood pressure disorders and diabetes. By continuously monitoring vital signs and contextual data—including daily activities and ambient environmental conditions—the system enables caregivers, clinicians, and healthcare facilities to deliver more responsive and informed care to patients residing at home. This approach aligns with current U.S. healthcare goals of expanding telehealth services, reducing hospital readmissions, and improving chronic disease management through personalized, technology-driven interventions.

The experimental results demonstrate that the framework consistently performs well across various health status classifications, including emergency, alert, warning, and normal states. Unlike traditional models that rely solely on cloud-based processing, this system is capable of making local decisions with high accuracy, ensuring uninterrupted service even in environments with limited or inconsistent internet connectivity—a common concern in many rural parts of the country. This local processing capability is particularly valuable for enabling immediate response in critical situations.

What sets this framework apart is its ability to integrate both personalized and general medical rules, making it robust across diverse patient profiles. Its offline functionality ensures fault tolerance, allowing it to operate effectively in the absence of cloud services while maintaining strong learning performance. The model is also context-aware, adjusting its recommendations based on a combination of patient behaviors and environmental data, which enhances the relevance and precision of its alerts. Built using a high-performing deep learning architecture, the system handles large volumes of unstructured and imbalanced health data efficiently and accurately.

From a technical perspective, the framework demonstrates scalability and adaptability. It is capable of managing extensive health data streams through the power of deep learning while remaining compatible with a wide range of modern technologies such as cloud computing, machine learning, and Internet of Things (IoT) devices. Its adaptive nature ensures that it can evolve with ongoing advances in health technology and data analytics, supporting long-term deployment in diverse care settings across the United States.

Looking forward, there are several promising directions for expanding the framework. Future versions may integrate Convolutional Neural Networks (CNNs) or other advanced deep learning models to enhance pattern recognition and classification capabilities. The framework's context-aware design also makes it a strong candidate for expansion into the monitoring of other chronic illnesses, such as cancer and neurological disorders, where continuous observation is critical. Additionally, incorporating cloud-based social networking services could provide an added layer of patient engagement and community support. Further research will focus on evaluating the framework's quality of service, energy efficiency, and performance metrics in cloud-based environments to ensure it meets the rigorous standards expected in modern healthcare delivery across the United States.

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