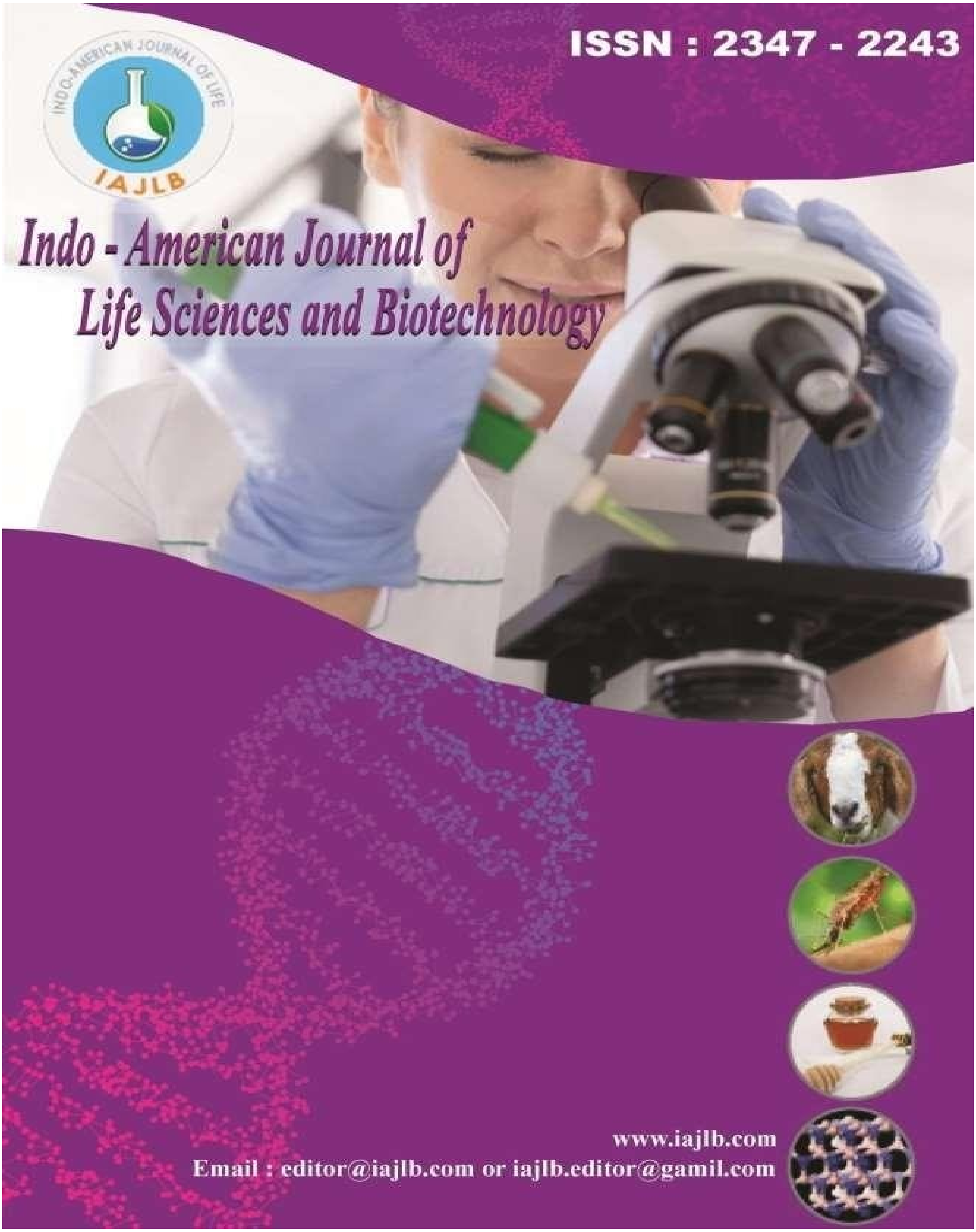
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Efficient Remote Patient Monitoring Using Multi-Parameter Devices and Cloud with Priority-Based Data Transmission Optimization

[1]**Durai Rajesh Natarajan**
Estrada Consulting Inc, California, USA
durairajeshnatarajan@gmail.com

[2]**Aravindhan Kurunthachalam**
Assistant professor
SNS College of Technology,
Coimbatore, Tamil Nadu, India.
kurunthachalamaravindhan@gmail.com

Abstract

Increasingly, cloud computing is transforming how data is managed and analyzed financially, providing scalable and secure solutions for SMEs and healthcare applications. Nevertheless, the remote patient monitoring (RPM) systems that have been established thus far encounter problems such as high latency, a poor usage of available bandwidth, as well as vulnerabilities in data security, thus restricting healthcare decision-making in real-time. Traditional encryption and authentication methods do not hold enough value against new-age evolving cyber threats and thus risk patient data privacy, whereas established means of data transmission do not prioritize significant health parameters leading to bring about delayed emergency response. E-RPM revolves proposing a very cost effective and safe Remote Patient Monitoring system on an integrated multi-parameter wearable device, cloud computing, and priority-based optimization of data transmission process for real-time health monitoring. Threats are detected using AI on hybrid encrypted data and then authenticated through multiple factors so that the system provides integrity of data as well as patient privacy and secured communication. The crux of this includes noise reduction and normalization of health data preprocessing, compression of data for high efficiency in storage and transmission, then the last nugget would be Convolutional Neural Networks (CNN) for predictive health analytics. It decreases congestion and proposes a priority-based transmission model which utilize bandwidth for real-time delivery of critical health data and reduced latencies.

Keyword: Cloud Computing, Remote Patient Monitoring, AI, Cybersecurity, Data Transmission Optimization, Convolutional Neural Networks (CNNs), Multi-Parameter Wearable Devices.

1.Introduction

Cloud computing is a revolutionary antidote for SMEs, which improves their functioning and strategic decision-easing in management accounting. This was also meant for re-organization of their data management, financial reporting, and analytics [1]. With the rise in complexities of financial datasets, machine learning techniques like GBDT, ALBERT, and Firefly Algorithm are incorporated into cloud architecture to support real-time processing, scalability, and secure computations [2]. These will integrate widely used mobile devices because of other cure ingress into multi-dimensional design of highly secured environments with sensitive data: the Comprehensive Approach for Mobile Data Security using the RSA Algorithm. Smart cities: explosive proliferation of IoT devices, creating volumes of real-time data, which become increasingly difficult to manage using traditional centralized systems because of high latency and inefficient consumption of resources [3]. Time series forecasting is vital for manufacturing, but the challenge has remained that the predictive systems are nonlinear and non-stationary. So advanced analytical models are needed for better accuracy and efficiency.

The development in Robotic Process Automation will completely change financial management by making it repetitive, error-free, and giving real-time reports while assessing effectiveness with cost accounting and financial systems [4]. The coming together of big data analytics, cloud computing, and attribute-based encryption further serves to secure financial data with an application of ABE: a technique for fine-grained access control over the encrypted data, using approaches like ciphertext-policy ABE (CP-ABE) and key-policy ABE (KP-ABE). However, cloud computing pleased the IT world while bringing cost-effective scalable solutions [5]. Small and medium enterprises face challenges selecting desired cloud services, and these have found their way on a new cloud brokerage schema employing B-Cloud-Tree indexing structure. Advanced prediction modeling is necessary for quickly arriving data in health care since, as the amount of data increases to billions of data points and terabytes, it will significantly improve patient outcomes with Stochastic Gradient Boosting, Generalized Additive Models, Latent Dirichlet Allocation, and Regularized Greedy Forest [6]. It integrates CatBoost to manage categorical data, ELECTRA for text analysis, t-SNE for dimensionality reduction, and Genetic Algorithms for optimization into a cloud-based structure that supports financial data analysis to address non-linearity, noise, and high-dimensionality. A hybrid approach based on Super Singular Elliptic Curve Isogeny Cryptography (SSEIC) and Gaussian Walk Group Search Optimization (GWGSO) as well as Multiswarm Adaptive Differential Evolution (MSADE) will thereby resolve the possible data breaches in IoT systems [7]. This is extended through isogeny-based hybrid cryptography, anisotropic random walks (ARW), and decentralized cultural co-evolutionary optimization (DCCO). Fog computing would eradicate the problem inherent in cloud-based IoT applications by improving both latency and performance: a new hybrid DBSCAN and fuzzy C-Means ABC-DE optimization has been proposed as a contribution to secure data sharing and resource allocation. Integration of these two approaches for security in data sharing is through secure IoT with PLONK and Infinite Gaussian Mixture Models (IGMM) for dynamic load balancing to avoid scalability, efficiency, and security-related issues [8]. Financial analysis embraces Monte Carlo simulations, Deep Belief Networks (DBNs), and Bulk Synchronous Parallel (BSP) through the cloud infrastructure for benefiting accurate financial forecasting since it would be scalable, secure, and high performance in data processing.

The chains of abstract models on complex networks have found application in almost all fields such as DNA study, physics, and even computer science, along with medicine, where they help convert recorded fractal geometry and graph theory into DNA sequences through different methods, which include nucleotide conversion, graph construction, Hurst exponent estimation, application of fractal geometry, and computation of the properties of networks [9]. Integration in real-time monitoring and diagnosis, within a hybrid learning model and neural fuzzy system, is made possible with the use of cloud computing, artificial intelligence, and the Internet of Things (IoT) in the healthcare sector, combined with the ability to address uncertainties in huge amounts of data created via IoT solution [10]. Such developments are expected to be witnessed in very few sectors regarding the incorporation of cloud computing presently with smart networks and even blockchain technology into e-commerce and finance sectors for efficient evolution in scalability, security, and efficiency [11]. Despite developing clinical care, heart failure (HF) continues to be a significant health challenge, increasing the demand for improved predictive models. Further, artificial intelligence (AI), machine learning (ML), and blockchain are defined as the keywords that will shape the future of human resource management (HRM), offering robustness in data security, predictions through predictions, and automation against the risks of traditional centralized HR systems-those that are susceptible to breaches and inefficiencies [12].

2. Literature Review

Thirusubramanian et al. attempts to promote a much more robust set of AI-driven approaches for real-time fraud detection in IoT data streams with advanced anomaly detection, clustering, and machine learning algorithms, which also promise high adaptability, frequent retraining, and automated-response mechanisms for improving accuracy [13]. They also introduced the P2DS security framework for financial institutions, combining Attribute-Based Encryption (ABE) and Attribute-Based Semantic Access Control (A-SAC) with the Proactive Determinative Access (PDA) algorithm to secure precise access control while enabling rapid threat detection and having high encryption efficiency [14]. Ganesan et al. describe a service-oriented architecture (SOA) running on a Hadoop-managed server cluster, allowing massive concurrent accessibility and high data throughput for educational resource management and distance learning with stress-testing supporting load reliability. They have also created a holistic assessment of the vulnerabilities IoT systems show at their core and done security implementations such as intrusion detection, encryption, access control, and frequent audits. Yallamelli et al. then present an advanced architectural framework to function via an interface with sophisticated AI, such as Random Forest classifiers, Transformer Networks, and TCN to have the distributed processing using cloud computing, cloudlets, and edge layers, facilitated with the use of Apache Flink for real-time stream analytics and blockchain to ensure the secure exchange of data [15].

Yallamelli et al. propose the Dynamic Mathematical Hybridized Modeling Algorithm (DMHMA), which integrates a tabular search (TS) algorithm that optimizes warehouse order patching along with operational efficiency [16]. Devarajan et al. construct a secure on-Internet of Medical Things (IoMT) and blockchain heart disease monitoring system applying both BS-THA and OA-CNN that guarantees the secure transfer of data, authentication, and accurate classification of the heart disease. Furthermore, they develop a completely different way of solving JSP using a Heterogeneous Genetic Algorithm (HGA) combined with Hybrid Particle Swarm Optimization (HPSO) to provide improved job sequencing and production time in regard to an enhanced search efficiency [17]. Besides, Devarajan et al. propose a federated learning and cloud-edge collaborative system for threat classification with a multi-national validation framework utilizing an end-to-end privacy-preserving deep learning (E2EPPDL) approach for security enhancement. Ganesan et al. present a DLaaS architecture in the vehicular environment that couples deep learning and network slicing for proactive resource management through dynamic allocation and improved network intelligence with capabilities to optimize traffic performance and customer satisfaction [18].

Ganesan et al. develop a hybrid approach to resource allocation and task scheduling based on Improved Bat Optimization Algorithm (IBOA) with dynamic weights and enhanced searchability complemented by Modified Social Group Optimization (MSGO) with an improved acquiring phase. Using multiple setups, this apparatus recorded success on improving efficiency responses regarding resource utilization and energy consumption, at 32.5 watts for 100 tasks, among others [19]. Devarajan et al. develop a comprehensive security management system in the cloud setting as applied to healthcare with several security services, such as security risk assessment, authentication, encryption, and intrusion detection as solutions to security threats [20]. Also, a Nash equilibrium-based approach on optimizing cloud resources in service delivery by strategic alignment of users and providers is presented under validation with real-world data. Devarajan et al. examined cardiovascular risk prediction in rheumatoid arthritis populations by studying biomarker stability, lipid profiles, and RA-specific markers using advanced biobanking, wearables, and telemedicine in personalization of therapies. Further, a system integrating image feature extraction with PSP Net, the analysis of non-linear brain signals with the Hilbert-Huang Transform (HHT), and fuzzy logic for classification adjustment is described to improve accuracy in classification and different disorders [21].

Devarajan et al. and co-workers advanced the securities concerning a hybrid data-mining scheme whereby association rule mining, decision tree classification, and neural network could be merged to automate the real-time processing of TBM data, thus enhancing the operational efficiency and safe management of tunnel projects [22]. They also created a method known as the Merged Cyber Security Risk Management (m-CSRM) for systematic risk assessment in which contextual threat intelligence, analyses of attack trends, fuzzy set mechanisms, and machine learning were amalgamated to raise the bar on cyber security [23]. The third development they created was a Recurrent Rule-Based Feature Selection (RFS) model to enhance Network Intrusion Detection Systems (NIDS) for securing IIoT systems through the use of NSL-KDD and UNSW-NB15 datasets involving a hybrid rule-based feature selection and attack classification algorithm. Yallamelli et al. stressed the necessity for good security of the clouds, proposing the RSA algorithm to safeguard the data through encryption and decryption based on prime factorization principles so as to allow for secure communication. They further assessed the immediate clouts on issues of cloud security: data integrity, unauthorized access, and privacy, through the Analytic Hierarchy Process (AHP), establishing data integrity as the primary one, finally recommending advanced encryption, AI-based threat detection, multi-factor authentication, and real-time monitoring to fortify cloud security.

3. Problem Statement

Increasingly sophisticated cyber-threats, significantly higher numbers of cloud security risks, and real-time data processing challenges need advanced solutions [24]. Traditionally, intrusion detection, risk assessment, and secure communication have struggled with these matters. This research has merged hybrid data mining, AI-based threat detection techniques, encryption, and multi-factor novel authentication to enhance security, data integrity, and efficiency-operational aspect over cloud computing, IIoT, and TBM systems [25].

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3.1 Objective

By making an Efficient Remote Patient Monitoring System incorporating multi-parameter devices and cloud computing involving optimization of priority-based data transmission, this research aims to develop such a system. Alongside addressing issues in cybersecurity threats, real-time data processing problems, and lack of secure communication, this system is to be integrated with AI-infused threat detection, hybrid encryption, and multi-factor authentication for enhancing data integrity, patient privacy, and seamless monitoring. Improved efficiency, scalability, and security in remote healthcare would allow for real-time decision-making and better outcomes from patients.

4. Proposed Remote Patient Monitoring Using Multi-Parameter Devices and Cloud with Priority-Based Data Transmission Optimization

The new RPM system includes multi-parameter wearable devices, cloud computing, and priority-based optimization of data transmission to enhance real-time monitoring of health through it. The devices would sense to monitor vital parameters and continuously collect value readings, while the readings will be sent to a secured cloud platform via a priority optimization-based transmission scheme. The health data critical for patient care would be pushed through in a low-latency fashion, while the rest of the routine nondelicate readings would be routed efficiently to reduce the footprint on the bandwidth. The framework will enable scalability and be interoperable so that real-time decision-making can be enabled in remote patient care and efficiency in health care will most benefit. AI-based anomaly detection, encryption techniques, and multi-factor authentication will acquire patient privacy, data security, and reliability and dependability for the system.

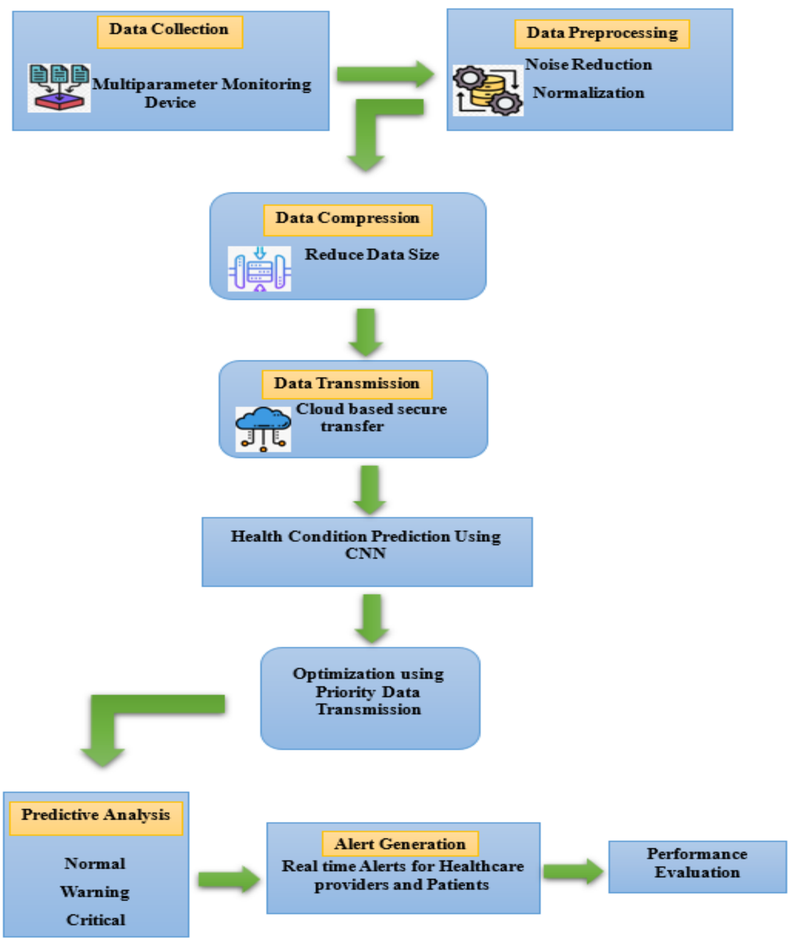

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Figure 1: Multi-Parameter Devices and Cloud with Priority-Based Data Transmission Optimization

4.1 Data Collection

Data collection takes place with the help of multiparameter monitoring devices that can continuously record vital parameters of health such as heart rate, blood pressure, oxygen saturation, temperature, and ECG signals, which may be in wearable or bedside devices. All these acquisition devices make available real-time monitoring of patients for the transmission of raw physiological data to be processed later. Such data will act as the primary ground upon which predictive analysis could be based to allow for trigger warnings and the early diagnosis of critical health states to be predicted.

4.2 Data Preprocessing

Raw health data will undergo noise reduction and normalization for improved accuracy and reliability during the preprocessing phase. Noise reduction techniques such as filtering and signal smoothing remove unwanted features and interference with sensor readings. Normalization scales data into a consistent range for uniformity across different parameters and sensor types and makes it significantly more efficient for further processing, thus leading to a more accurate prediction in health conditions.

4.2.1 Noise Reduction

The cleansing of noise improves the general quality of the signal, thereby reducing unnecessary fluctuations caused by the sensor reading, so increasing the accuracy of health monitoring. Typical algorithms used in data smoothing are wavelet transform or moving average filters, which maintain the features while smoothing the data.

Equation for Noise reduction:

$$Y(n) = \frac{1}{N}\sum_{i=0}^{N-1} X(n-i) \tag{1}$$

Where:

$Y(n)$ is the filtered output,

$X(n)$ is the original signal,

N is the window size for averaging.

4.2.2 Normalization

Normalization is the data value over which attributes fall and flattens different parameters before a particular framework within predictive models can be applied. It removes away variations that can be attributed to different sensor readings and enhances comparability amid data comparisons, cutting bias from analytical results.

Equation for Normalization: A common normalization technique is Min-Max scaling, given by,

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

Where:

X' is the normalized value,

X is the original value,

$X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the dataset, respectively.

4.3 Data Compression

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In the reduction of medical record data sizes for better storage and faster transfer to the Cloud. Lossless methods like Huffman encoding retain the quality of information. In contrast, lossy compression methods such as wavelet transform focus primarily upon removal of redundancy, which largely reduces bandwidth requirements and processing time.

4.4 Data Transmission

One of the benefits of transmitting health data via transmissions onto the Cloud must always be at a real-time pace to and from the patient and are carried out in such a way as to keep that data confidential and immune to any kind of alteration - typically with encryption mechanisms like AES and TLS. The other aspect of the tradeoff is provided perhaps on authentication mechanisms which bar unauthorized access and hence ensures that reliable efficient communication does occur amidst devices and other healthcare systems quite literally.

4.5 Health Condition Prediction Using Convolutional Neural Network (CNN)

CNNs on the other hand are deep learning-based architectures, and for this reason they are mostly used to process structured grid data, representing, for example, images and time series. They are comprised of convolutional layers for spatial or temporal feature learning, pooling for dimensionality reduction, and fully connected layers for further classification. In healthcare operations, CNNs synthetic signals which are electrocardiogram (ECG), photo plethysmo gram (PPG), and heart rate data alongside fully-integrated inter-parameter data for predictive analytics, secondary diagnostics, and anomaly detection.

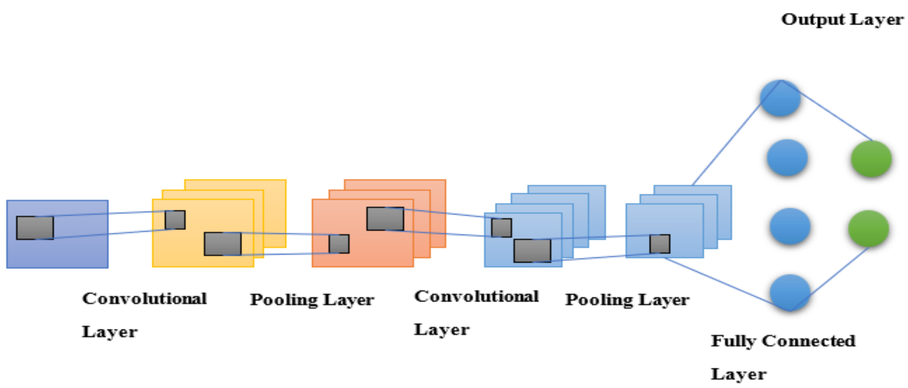

Figure 2: Architecture of Convolutional Neural Network

Equation for Convolutional Neural Network:

$$Z_{i,j} = \sum_m \sum_n X_{i+m,j+n} \cdot K_{m,n} + b \quad (3)$$

Where:

$Z_{i,j}$ is the output feature map,

X is the input data,

K is the convolution kernel (filter),

b is the bias term,

m, n are the filter dimensions.

This operation captures essential patterns in medical signals, improving diagnostic accuracy.

4.6 Priority Based Data Transmission for Optimization

The transmission patterns dependent on priorities help increase bandwidth optimization such that crucial healthcare-related information such as emergency alarms, vital signs, and anomalies are processed in good time nearly untouched in precedence over less important information. This methodology is intended to minimize latency associated with medical emergencies and to enable further optimal use of bandwidth and resources in cloud-based monitoring of patients. The assignment of priorities in this manner for various data types constitutes a critical allocation and reallocation of bandwidth access on-the-fly, ensuring that the most critical communications are not delayed while the non-critical workload faces some scrutiny.

Equation for Priority-Based Data Transmission:

$$T_d = \frac{S}{B} \times P \tag{4}$$

Where:

T_d is the transmission delay,

S is the data size,

B is the available bandwidth,

P is the priority weight factor ($P > 1$ for high-priority data, $P \leq 1$ for low-priority data).

This model ensures that high-priority medical data is transmitted faster, enhancing real-time patient monitoring and response efficiency.

5. Results and Discussion

With cloud-based secure transfer, the proposed Remote Patient Monitoring System collects, processes, and transmits patient data. CNN-based health prediction accurately classifies the condition as Normal, Warning, or Critical, ensuring timely intervention. Priority-based data transmission optimizes the bandwidth and minimizes latency to achieve real-time alerts. The performance evaluation demonstrated improved accuracy, reduced response times, and a better decision-making environment for healthcare.

Data Compression

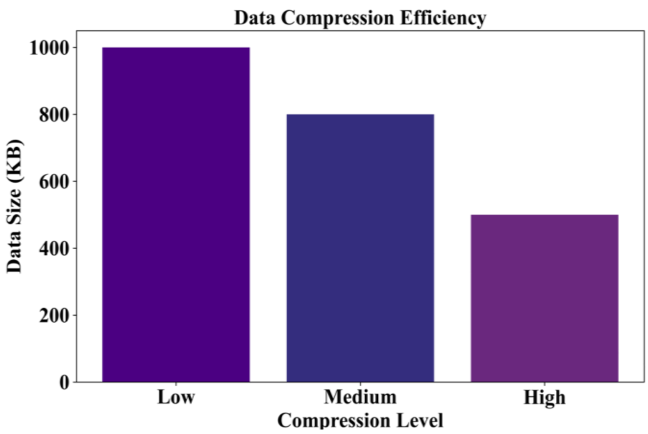

Figure 3: Data Compression

In Figure 3, The Data Compression Efficiency graph shows the compression levels (Low, Medium, and High) versus Size (in KB). With increasing compression level, the size of data kept on going down, representing improvement in terms of storage and transmission. The Low compression level puts in the largest data size around

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about 1000 KB, whereas the medium compression level cuts it down considerably, and High compression level puts it as low as possible for the sake of storage and bandwidth usage for cloud-based efficient data transmission.

Latency

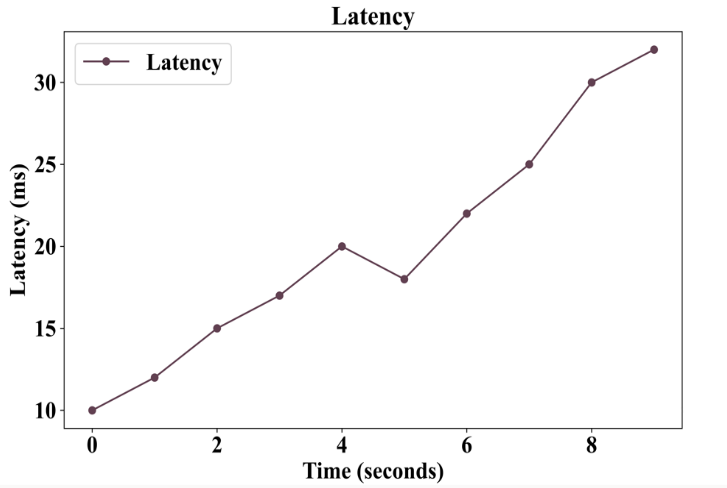

Figure 4: Latency

Figure 4 shows latency (in milliseconds) against time (in seconds). It shows an increasing trend indicating that as time increases, the latency also increases. This indicates possible network congestion or processing delays that may be affecting system performance.

Real Time Alerts

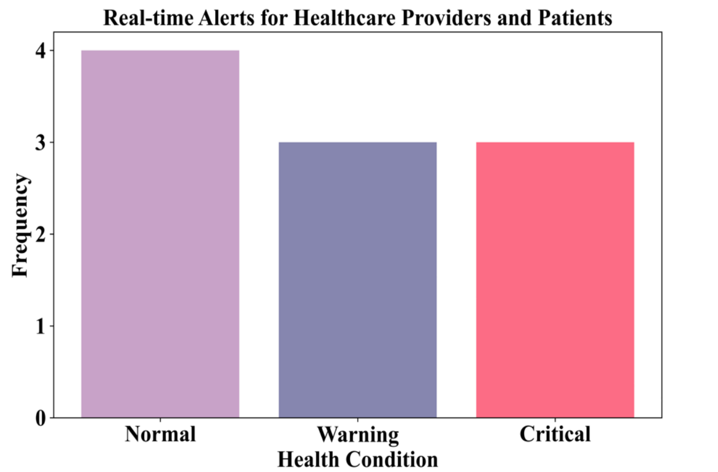

Figure 5: Real Time Alerts

Figure 5 shows the frequency of real-time alerts for Normal, Warning, and Critical categories. Normal alerts are the most frequent, followed by Warning and Critical alerts with similar albeit slightly lower frequencies. This indicates that most patients are stable, while some do require medical attention in time for healthcare intervention.

6. Conclusion

Remote Patient Monitoring System proposed is furthering healthcare at the level whereby it conveniently collects, processes, and transmits patient data through cloud and AI-based prediction. Priority-based transmission of data ensures real-time alert system with the enhancement of feedback mechanism and well-informed decisions. The results show improved accuracy, reduced latency, and better patient care outcomes.

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