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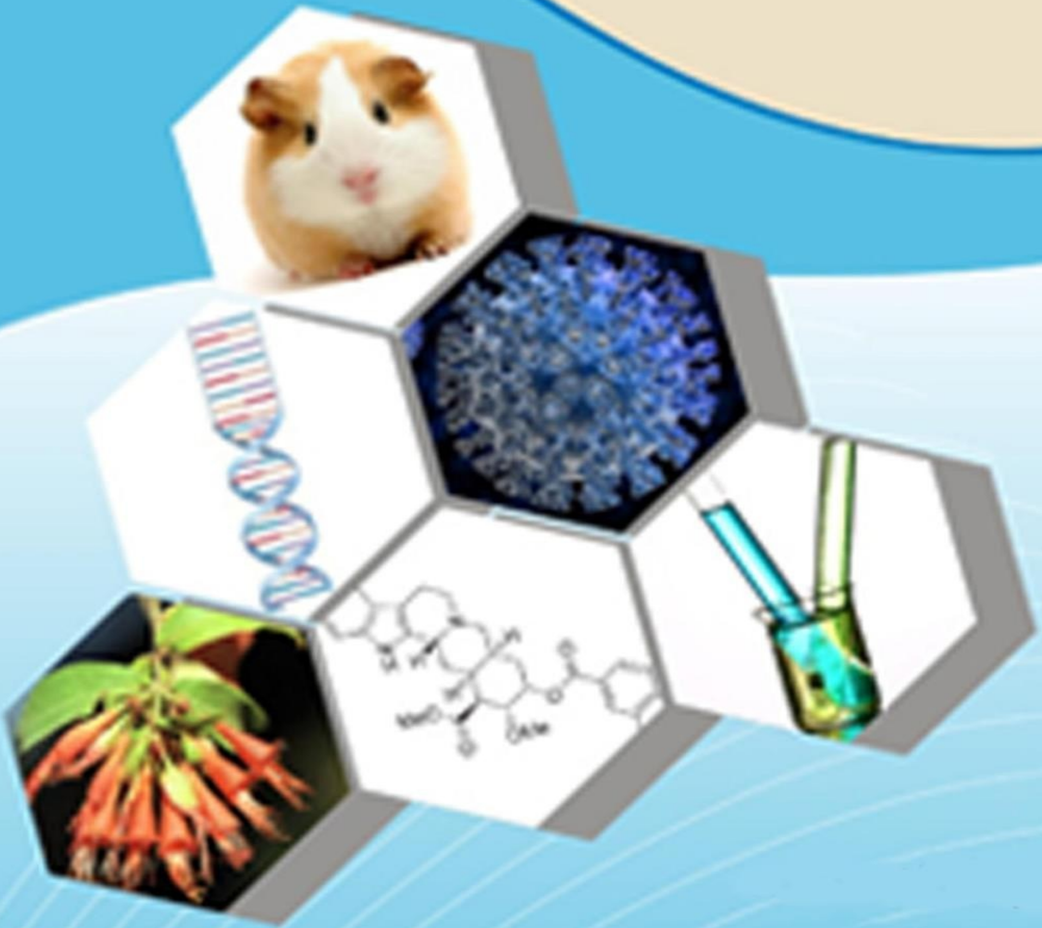

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CLOUD-BASED HEALTHCARE MONITORING SYSTEM FOR ABNORMAL HEALTH PATTERN DETECTION USING CONVLSTM

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ABSTRACT

The healthcare domain is increasingly adopting technology to enhance patient monitoring, diagnosis and treatment through data collection and advanced predictive analytics. Traditional systems struggle with delays in diagnosis and the inability to adapt to continuous changes in patient health, leading to suboptimal care. To address these problems, this work proposes to develop a cloud-based healthcare monitoring system that uses deep learning to detect abnormal health patterns, enabling early detection and timely intervention for potential health risks. The system begins with gathering healthcare data from medical records, wearable devices and IoT sensors. After that, data preprocessing follows, where missing values are handled using K-Nearest Neighbors imputation and outliers are detected using the Interquartile Range method for data consistency. Feature extraction is then performed using Discrete Wavelet Transform to decompose time-series data into frequency components, capturing both time and frequency features. The extracted features are fed into a Convolutional Neural Network with Long Short-term Memory (ConvLSTM) model, which combines convolutional layers to capture spatial patterns and LSTM layers for capturing temporal dependencies to classify the data as normal or abnormal. Finally, the trained model is deployed in the cloud, ensuring scalability, accessibility and continuous model updates through periodic retraining with new data. Results demonstrate that the system achieved an accuracy of 99.22%, precision of 99.34%, sensitivity of 98.58%, specificity of 98.23% and an F-Measure of 97.74%. Additionally, latency of 35 ms at 200 ms response time, highlighting the model's performance. The proposed approach offers an efficient, scalable solution for continuous patient health monitoring, providing accurate predictions, reducing the time to diagnosis and ensuring timely interventions for improved patient care.

Keywords: Healthcare Data, Cloud Storage, Abnormality Detection, Long Short-Term Memory and ConvLSTM.

1 INTRODUCTION

Continuous patient care integrated with technology has revolutionized a patient's healthcare due to its ability to monitor in real time and take decisions [1]. The development of the IoT devices, wearable health monitors and cloud computing have rapidly evolved towards the collection, storage and analysis of big health data [2]. This makes healthcare professionals able to take educated decisions regarding the better diagnosis, treatment and preventive measures for the disease, as well as to improve the use of data for decision making [3]. Moreover, predictive models and personalized patient care could become possible through machine learning and artificial intelligence, which further advance health care capabilities. With all these technologies, it improves and manages chronic diseases, raising overall health care outcomes with a more proactive approach to monitoring patients' health. The innovative DMHMA approach by Akhil Raj Gaius Yallamelli (2024) [4] influenced the current research by showcasing effective optimization in dynamic systems. This encouraged the adoption of hybrid modeling and cloud scalability for improving health data processing and anomaly detection.

Such factors include embracing the increasing demand for intelligent healthcare. The increasing aging population happens to be the greatest factor at its peak with the elderly having a higher propensity to chronic diseases that require constant monitoring. Lifestyle diseases are also increasing in number, the major ones being diabetes, obesity and other cardiovascular diseases; this ends up greatly exhausting the health care system [5]. Furthermore, other factors, such as sedentary lifestyle, poor nutrition and increased levels of stress, have led to occurrence of chronic health conditions in ever-growing proportions. Such diseases necessitate very effective monitoring, prediction and managing systems for the patient's health. Certainly, there is a high demand for better automated mechanisms which can analyze data in real-time and send early warnings on possible health risks.

It is in a level that most traditional methods of health care cannot be able to reach those volumes of patient-generated data, either in a static or dynamic state because of the nature of disease complexity [6]. Because of the nature of delayed detection of health conditions and the delays of interventions, it uses manual procedures like the old methodology of intermittent patient check-ups. In addition to this, a paper-based system or rather an outdated digital record adds to the non-facilitating cross-usage of health data between multiple providers at reduced effectiveness and efficiency. These methods are born with limitations in terms of misdiagnosis, missed opportunities for early intervention and overall inefficiency in the distribution of resources. With the evolution of the health systems, much progress has been made toward their transition to cloud computing platforms and AI modeling, which, indeed, offer real-time monitoring and predictive analytics to improve patient care.

The rapid advancement of wearable devices and IoT technologies has revolutionized healthcare monitoring by enabling continuous collection of vital health data. Accurate analysis of this data is crucial for early detection of abnormal health conditions and timely medical intervention. The advance use of robotic automation and AI models by Surendar Rama Sitaraman (2024) [7] stimulated this proposed work's focus on accurate patient monitoring. His success prompted adopting scalable ConvLSTM architectures for improved abnormal health pattern detection. However, raw healthcare data often contains missing values and outliers, which can affect model reliability if not properly preprocessed. This paper proposes a robust healthcare monitoring framework that leverages K-Nearest Neighbors (KNN) imputation and Interquartile Range (IQR) methods to handle missing data and outliers, ensuring high data quality. Feature extraction is performed using Discrete Wavelet Transform (DWT), capturing important time-frequency characteristics of physiological signals[8] [9].

The core predictive model employs a hybrid Convolutional Long Short-Term Memory (ConvLSTM) network, combining spatial and temporal analysis to recognize patterns in complex sequential healthcare data. This hybrid approach enhances the model's ability to differentiate normal from abnormal conditions in patients effectively. Furthermore, the trained model is deployed on a scalable cloud platform, facilitating real-time health monitoring and prediction while ensuring secure and seamless access for healthcare providers. This cloud deployment enables efficient handling of large-scale data streams from multiple patients and devices. Overall, the proposed methodology presents an efficient and scalable solution for predictive healthcare monitoring, integrating advanced preprocessing, feature extraction, and deep learning techniques to support better clinical decision-making and patient care [10].

Wearable health devices generate massive amounts of time-series data such as heart rate, blood pressure, glucose levels, and other vital signs, which reflect a patient's health state dynamically. Effectively analyzing this multivariate sequential data presents challenges due to noise, missing readings, and temporal dependencies. Addressing these challenges is critical for delivering reliable healthcare analytics that can predict potential abnormalities before they escalate. Traditional machine learning methods often fall short in modeling the complex spatial-temporal relationships inherent in physiological signals. Deep learning models, especially architectures like ConvLSTM, have shown promise in capturing both local spatial features and long-term temporal patterns, making them well-suited for healthcare applications involving sequential sensor data. Their ability to learn hierarchical representations enables better pattern recognition from noisy and incomplete datasets.

The use of Discrete Wavelet Transform (DWT) as a feature extraction tool further enhances model performance by decomposing signals into time-frequency components, allowing the identification of transient and sustained anomalies in vital signs. Statistical features derived from wavelet coefficients, such as mean, variance, skewness, and kurtosis, provide robust indicators for detecting abnormal physiological events. Integrating preprocessing, feature extraction, and deep learning within a cloud-based framework not only ensures high computational efficiency but also supports scalability for widespread adoption. Cloud deployment enables continuous model updates, data centralization, and accessibility from diverse healthcare settings, including remote and resource-constrained environments, which is vital for real-world applicability.

This research thus aims to contribute a comprehensive healthcare monitoring system that combines state-of-the-art data handling, advanced feature engineering, and deep learning methodologies with cloud computing. Such an integrated system promises improved prediction accuracy, robustness to data irregularities, and practical usability in modern healthcare ecosystems, ultimately enhancing patient monitoring and outcomes.

The structure of the paper is as follows: Section 2 provides a literature survey, reviewing existing methods. Section 3 describes the methodology. Section 4 presents the results and performance metrics and Section 5 concludes the paper.

2 LITERATURE SURVEY

With advances in point cloud learning, new architectures have been developed to address specific problems of irregularity and lack of order characteristic of the nature of data that originates from point clouds. PCT further compresses sequences of points into a permutation that can thus help farthest point sampling and nearest neighbor search in augmenting the capturing from local contexts. Another disadvantage of PCT is that it has state-of-the-art results for object shape classification and segmentation, but due to its high computational cost, it cannot be scaled up much for larger point cloud datasets. Fast changes have led to the evolution from the original thought of an internetwork service that could be leased by ISPs, hence being termed a public utility, down to its acceptance by major corporations, large institutions and most government entities.

Among the major milestones on this path are the 2003 seminal papers from Google and their subsequent establishment of a commercial service in 2006 via Amazon EC2. It is not only cost-saving measures that are driving cloud computing today, but it is also gaining a certain notoriety as a get-rich-quick potential. The paper further dwells on the definition, trajectory, advantages and disadvantages, the value chains and some of the standardization initiatives undertaken along the way. The effective dimensionality reduction and cognitive mapping techniques in Dinesh Kumar Reddy Basani (2024) [11] research prompted the feature extraction and decision-making components of this study. Building on these ideas, this work leverages DWT and ConvLSTM for precise health anomaly detection.

The application of cloud computing in organisations has been discussed in depth in the course of this study that is illustrated in the case studies in order to appreciate their technological innovations and salient features of the technology. Besides this, the study sheds light on types of challenges those exist in security and intrusion detection systems in the present field and what could be future research directions on challenges brought to face business environments by cloud adoption [12]. Practically, clouds have been served and have gained acceptance within the various sectors of industries, individuals and society in general since the year 2019. Most likely because of the on-demand use and low spending attributed to it, security became that major issue, making all the three tiers of security-IaaS, PaaS and SaaS levels faced with a very strong challenge throughout the year 2020.

This particular research attempts to present a thumbnail sketch of security in clouds across the past decade. However, the original field of this study is itself confined within the atmosphere of rapid technological advancements in relation to clouds and destined to face increasing security concerns over time. IIoT cannot handle huge data created from IIoT, where the scenario comes from power and storage constraints only. This is self-organizing and short-range IoT networking fueled by a solution where cloud computing could be restoring data out of some constraints of the device. The research focuses on hitches and algorithms which easily meshed IoT with cloud computing addressing both efficiency in cloud applications as well as modern interpretation of semi-structured storage forms.

These are words by Ganesan Thirusubramanian in an article called "AI-ML Detection on Fraud in Finance", about IoT in pure terms. The new algorithms, specifically the anomaly and cluster-based algorithms whose application could analyze streams of IoT events generally looking for possible undesired activities, are presented in the paper. Training improvement in the process of the supervised and unsupervised learnings using historical transactions was included for fraud detection.

Adaptive retraining techniques and automatic fraud event responses have strengthened credibility for this. Poor quality data and computational complexity, along with the highly dynamic shifts in the whole fraud environment, affected the detection capabilities remarkably [13]. Ganesan has developed service-oriented architecture for that system to run on a Hadoop-managed server cluster for processing power and at the same time keeping the data storage intact. So, it actually looks after remote educational resources which hold quite large data and concurrency very well. Stress tests proved that it would be highly reliable supporting many thousands of simultaneous end-users-well into the range of many millions of transactions in heavy loads [14].

The hybrid IoT-integrated framework utilizes edge AI together with cloud computing, which was very recently found by Yallamelli et al. as the intelligent data processing solution for health data. The research work is all about security towards data sharing, decreased latent times and improved process quality for decision making. Advanced AI such as Random Forest classifiers, Transformer Networks and Temporal Convolutional Networks employed herein contributed to this model. All of these led to the distributed processing all over the system through cloud computing, cloudlet and edge layers. Stream analytics is carried out in real time through Apache Flink while secure information exchange is realized through the blockchain.

These all seem to be a few of the achievements; this study also mentioned about high computation costs, integration problems and bottleneck for large-scale data processing as limitations with such works. Reference narrowed down IoT security using critical node identification, invasive assessment, security measures and total system performance impact analyses. One such approach included quantification in assessing vital IoT system components after sufficient vulnerability assessment. An intrusion detection system was also suggested along with a number of encryption tools, access control methodologies and frequent security audits to check the sensitivity of each method in the overall security of IoT systems.

Point cloud learning has rapidly evolved to address challenges such as irregularity and lack of order inherent in 3D point cloud data. The Point Cloud Transformer (PCT) architecture compresses sequences into permutations to enhance local context understanding through farthest point sampling and nearest neighbor search. While PCT achieves state-of-the-art results in object shape classification and segmentation, its high computational cost limits scalability for large datasets, highlighting the need for more efficient models.

Cloud computing has transformed from a concept of leased internetwork services to an essential infrastructure embraced by corporations, governments, and institutions worldwide. Key milestones include Google's seminal work in 2003 and Amazon EC2's commercial launch in 2006. Beyond cost savings, cloud computing has become a lucrative industry. Studies emphasize its advantages, including scalability and resource optimization, while acknowledging challenges such as security risks and standardization efforts.

The application of cloud computing in organizations has been well documented through case studies demonstrating technological innovation and adoption. Despite widespread use across sectors, security and intrusion detection remain critical challenges, particularly at IaaS, PaaS, and SaaS levels. Research highlights ongoing efforts to strengthen security frameworks to address vulnerabilities and the dynamic threat landscape that cloud adoption introduces. The Industrial Internet of Things (IIoT) faces significant challenges due to power and storage constraints, limiting its ability to handle large data volumes. Cloud computing emerges as a solution by offloading heavy processing and storage demands from constrained devices. Recent studies focus on efficient algorithms that integrate IoT with cloud platforms to improve data management and application efficiency, leveraging semi-structured data storage techniques for better scalability. Dharma Teja Valivarthi's (2024) [15] hybrid detection framework underscored the critical role of multi-domain data integration for timely and accurate identification. This reinforced the spotlight on optimizing data fusion and feature extraction methodologies in the proposed research.

In the realm of fraud detection in finance, Ganesan Thirusubramanian's work explores anomaly and cluster-based algorithms to analyze IoT event streams for undesirable activities. His hybrid system uses supervised and unsupervised learning to improve detection over historical transaction data, supplemented by adaptive retraining and automated fraud responses. Deploying this system on Hadoop clusters ensures high computational power and data reliability, supporting millions of transactions and concurrent users.

Hybrid IoT-cloud frameworks incorporating edge AI have gained traction for healthcare data processing. Yallamelli et al. demonstrate a secure, low-latency solution employing Random Forests, Transformer Networks, and Temporal Convolutional Networks distributed across cloud, cloudlet, and edge layers. Real-time stream analytics through Apache Flink and blockchain-enabled secure information exchange are key features, although challenges such as high computational costs and integration bottlenecks remain [16].

IoT security continues to be a focal area, with studies proposing critical node identification, vulnerability assessments, and comprehensive security measures. Intrusion detection systems combined with encryption, access control, and periodic security audits are suggested to bolster system robustness. Quantification of sensitivity and impact analyses of security methods provide a systematic approach to enhancing overall IoT network security.

Research on large-scale cloud and edge computing architectures reveals inherent limitations in computational costs and system integration complexities [17].

Bottlenecks in data processing and interoperability hinder seamless deployment across diverse IoT applications. These constraints necessitate optimized frameworks balancing performance, scalability, and security to handle ever-growing IoT-generated data.

Emerging AI techniques such as transformer-based models and temporal convolutional architectures show promise in modeling complex, temporal IoT data patterns. Integrating these with cloud and edge layers supports distributed, scalable analytics. Nonetheless, addressing trade-offs between latency, accuracy, and computational resources remains an ongoing challenge for real-world applications. Overall, the literature underscores the convergence of IoT, cloud computing, and AI as a transformative force in various domains, especially healthcare and finance. While significant progress has been made in algorithm development and system design, key issues related to scalability, security, and cost-efficiency continue to motivate research toward more adaptive, integrated solutions capable of managing large-scale, heterogeneous data environments [18].

2.1 Problem Statement

Despite considerable advancements in healthcare technology and predictive modeling, several critical challenges persist that limit the effectiveness and sustainability of these solutions. One major issue is model drift, where the performance of predictive models progressively deteriorates over time due to changes in patient populations, disease patterns, or data distributions. Without effective adaptation mechanisms, these models become outdated and fail to provide accurate and reliable predictions. This degradation can negatively impact clinical decisions, potentially leading to missed diagnoses or inappropriate treatments. Therefore, continuous monitoring and timely updating of models are essential to maintain high predictive accuracy and clinical relevance in dynamic healthcare environments. Another significant barrier is the limited access to advanced healthcare monitoring and early diagnosis, particularly in underserved and resource-constrained regions. Many patients in deprived areas face challenges such as inadequate healthcare infrastructure, lack of specialist availability, and irregular follow-up care, which widen health disparities and delay critical interventions. The proposed cloud-based healthcare monitoring system aims to bridge this gap by integrating scalable, adaptive predictive models with cloud computing technologies. Rajani Priya Nippatla (2024) [19] emphasizes secure, decentralized data exchange using DAG-based blockchain to ensure data integrity and privacy. Influenced by this, the proposed medical surveillance system incorporates scalable cloud architecture and robust data security measures.This approach facilitates continuous model adaptation and real-time predictions, ensuring that healthcare solutions remain accurate, up-to-date, and accessible across diverse populations. By leveraging cloud infrastructure, the system can extend high-quality healthcare monitoring and early disease detection to a broader audience, ultimately supporting more equitable and proactive patient care.

3 METHODOLOGIES

The architecture of the proposed healthcare monitoring system is illustrated in Figure 1. The methodology is initiated with data collection, which is a critical phase in ensuring comprehensive monitoring. Healthcare data is acquired from a variety of sources, including electronic medical records (EMRs), clinical repositories, and IoT-enabled wearable devices such as fitness trackers and health monitoring sensors [20]. These wearables continuously record physiological parameters like heart rate, blood pressure, glucose level, oxygen saturation, and physical activity, transmitting them to the central processing unit. The data preprocessing stage follows, aimed at improving data quality and preparing it for effective analysis. To address missing values, the K-Nearest Neighbors (KNN) imputation method is employed. KNN estimates missing entries by evaluating the similarity between data instances, thereby ensuring that the imputed values reflect real-world trends. To ensure robustness, outlier detection is carried out using the Interquartile Range (IQR) method, which identifies and removes data points that deviate significantly from the majority of the dataset, thus enhancing the reliability of subsequent computations [21].

Once preprocessed, the data undergoes feature extraction using the Discrete Wavelet Transform (DWT). DWT is a powerful tool for analyzing signals in both time and frequency domains, enabling the model to capture transient changes in health signals that may indicate early signs of abnormality. This dual-domain analysis is essential for detecting subtle variations in physiological data that might be overlooked by traditional time- or frequency-based methods alone. The extracted features are then fed into a Convolutional Long Short-Term Memory (ConvLSTM) network. This hybrid deep learning model combines the spatial feature extraction capabilities of Convolutional Neural Networks (CNNs) with the temporal pattern recognition strengths of LSTM networks [22]. The ConvLSTM effectively learns from the sequential patterns and spatial correlations within the health data to classify the state as either normal or abnormal. This classification result is subsequently stored in a cloud-based infrastructure, which enables remote access, continuous updates, and real-time analysis by healthcare providers.

Overall, this methodology offers a robust, accurate, and scalable solution for healthcare monitoring. It effectively integrates advanced signal processing techniques, deep learning models, and cloud computing technologies to ensure comprehensive patient health tracking and anomaly detection across a wide range of data sources and volumes.

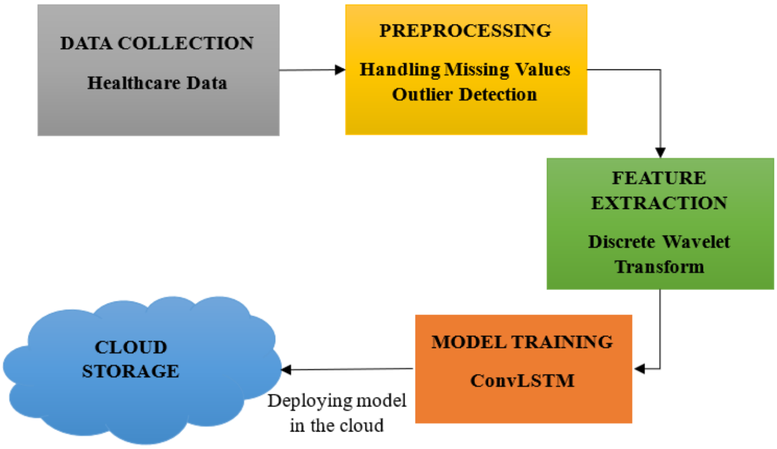

Figure 1: Architecture of the Proposed Healthcare Monitoring System

3.1 Data Collection

In the proposed healthcare monitoring framework, data collection plays a foundational role in ensuring reliable and accurate predictions. The system aggregates health-related data from multiple sources, primarily IoT-enabled wearable devices and Electronic Health Records (EHRs). The wearable devices include heart-rate monitors, glucose meters, fitness trackers, and temperature sensors, which are designed to continuously capture real-time physiological signals from patients. These devices provide vital health indicators such as heart rate, blood pressure, blood glucose level, body temperature, and oxygen saturation. In parallel, Electronic Health Records serve as a repository of historical and clinical data, including previous diagnoses, prescribed medications, laboratory results, immunization records, and lifestyle information such as physical activity levels, smoking habits, and dietary patterns [23]. By integrating EHRs with live sensor data from wearable devices, the system achieves a holistic and contextual understanding of the patient's health status. The quality, accuracy, and completeness of the collected data are pivotal to the performance of the subsequent stages in the pipeline. Incomplete or inconsistent data can significantly compromise the effectiveness of data preprocessing, feature extraction, and model training, leading to inaccurate predictions. Therefore, mechanisms are embedded in the system to ensure timely acquisition, synchronization, and validation of data from heterogeneous sources. Driven forward by these insights, the proposed work seeks to reduce delays and enhance precision in healthcare monitoring system implementations, as demonstrated by Kannan Srinivasan (2024) [24], who established that combining low latency and accuracy improves decision-making in robotic-assisted operations. This comprehensive and high-fidelity data acquisition framework enables the healthcare monitoring system to make precise health condition classifications and predictive assessments, allowing for early detection of abnormalities and timely medical interventions. The integration of continuous real-time data with longitudinal health records empowers clinicians to make informed decisions and enhances the overall quality of patient care.

3.2 Preprocessing

3.2.1 Handling Missing Values

Following the initial phase of data collection, the dataset may contain missing values, which are common in healthcare data due to sensor malfunctions, manual input errors, or incomplete patient records. Addressing these missing values is essential to ensure the integrity and reliability of downstream analytical processes. To handle this, the K-Nearest Neighbors (KNN) imputation method is employed [25]. KNN imputation operates by identifying the 'k' most similar instances (neighbors) within the dataset based on the available attributes. The similarity is typically measured using distance metrics such as Euclidean distance for numerical data. For each missing value, the algorithm estimates it by computing the average (or most frequent value, in the case of categorical data) among the corresponding attribute values from the k nearest neighbors.

This technique is particularly advantageous in healthcare datasets as it preserves the inherent structure and distribution of the data [26]. Unlike mean or median imputation methods, which can introduce bias and reduce variance, KNN imputation provides context-aware estimations, thus maintaining the representational richness of the data. It minimizes distortion and avoids introducing artificial patterns, making it well-suited for high-dimensional and heterogeneous medical datasets. By completing the dataset through KNN imputation, the system ensures that no valuable information is discarded, enabling accurate feature extraction, model training, and prediction in the subsequent stages. This results in a more robust and generalizable healthcare monitoring model.

3.2.2 Outlier Detection

In addition to addressing missing values, the dataset undergoes outlier detection to further enhance its quality and consistency. Outliers in healthcare data can arise due to sensor anomalies, patient non-compliance, data entry errors, or rare but extreme physiological variations. If left unaddressed, such outliers may distort the learning process of predictive models, leading to reduced accuracy and generalization. To mitigate this, the Interquartile Range (IQR) method is employed. This statistical technique identifies data points that fall significantly outside the normal range of values. Specifically, the IQR method considers values to be outliers if they lie beyond a certain distance from the central portion of the dataset, which is defined by the 25th percentile (lower quartile) and the 75th percentile (upper quartile). These bounds encapsulate the core distribution where most of the typical data points reside. The continuous surgical observation framework by Sathiyendran Ganesan et al. (2022) [27] significantly influenced the proposed work by emphasizing the importance of patient safety and resource allocation in dynamic medical settings through cloud-IoT integration.

Once identified, outlier values are either removed from the dataset or adjusted using appropriate strategies such as value capping or imputation based on neighborhood statistics. This process ensures that the remaining data used for feature extraction and model training is more reflective of the typical, expected patterns observed across the patient population. By eliminating extreme or inconsistent values, the system can learn more reliable representations of health conditions, thereby improving the robustness and predictive performance of the healthcare monitoring model [28]. Ultimately, the IQR-based outlier detection contributes to a cleaner dataset that promotes the development of accurate and interpretable machine learning models.

3.3 Feature Extraction

The pre-processed data is then used for feature extraction with DWT-based feature extraction, which decomposes time series data into time and frequency components. The technique can capture important patterns at various scales so that the analysis of health metrics fluctuating such as heart rate, blood pressure, or glucose can be carried out. Statistical features such as mean, variance, skewness and kurtosis, among others, are extracted from the transformed data. Such features identify key trends and abnormalities that provide the necessary information for the detection of health states [29]. This way, the model will learn more relevant and informative data, thus enabling prediction with greater effectiveness.

The main goal of DWT is to decompose a signal $x(t)$ into different frequency components, capturing both high and low-frequency information. The DWT is defined as equation (1),

$$W(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt \tag{1}$$

where, $W(a, b)$ is the wavelet coefficient at scale a and translation b. $\psi_{a,b}(t)$ is the wavelet function that is scaled and translated. a is the scale (which controls frequency) and b is the translation (which controls time). This equation breaks the signal into various components, each representing different frequencies at different times.

Once the signal is decomposed into wavelet coefficients, extract the features to describe the signal. These statistical features help in identifying patterns, trends and abnormalities in the data. The mean of the wavelet coefficients gives an average value over a certain time period. It indicates the general level of the signal and it's embodied as equation (2),

$$\text{Mean } = \frac{1}{N}\sum_{i=1}^{N} W(a_i, b_i) \tag{2}$$

where, N is the total number of wavelet coefficients. $W(a_i, b_i)$ represents the wavelet coefficient at scale a_i and translation b_i. The mean is used to understand the average value of the wavelet coefficients, helping to characterize the overall trend of the signal

Variance measures the spread or variation of the wavelet coefficients. It indicates how much the signal fluctuates over time and variance is represented as equation (3),

$$\text{Variance } = \frac{1}{N}\sum_{i=1}^{N} (W(a_i, b_i) - \mu)^2 \tag{3}$$

where, μ is the mean of the wavelet coefficients [30]. The variance gives an idea of how much the signal deviates from the mean. Variance is important for detecting variations in the health data, such as fluctuations in heart rate or blood pressure.

Skewness measures the asymmetry of the distribution of wavelet coefficients. It shows whether the distribution is skewed to the left or right. Skewness is expressed as equation (4),

$$\text{Skewness } = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{W(a_i,b_i)-\mu}{\sigma}\right)^3 \tag{4}$$

where, μ is the mean of the wavelet coefficients. σ is the standard deviation of the wavelet coefficients. Skewness helps to detect if there are any asymmetrical patterns in the signal, such as sudden peaks or drops in patient data. Narsing Rao Dyavani (2024) [31] highlights the functionality of combining Markov Models with Topological Data Analysis for adaptive, access control in cloud healthcare. This shaped the proposed approach toward dynamic, context-aware security and scalable data protection in healthcare monitoring mechanism.

Kurtosis measures the "tailedness" of the wavelet coefficients' distribution, indicating how outliers or extreme values are distributed. Kurtosis is represented as equation (5),

$$\text{Kurtosis } = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{W(a_i,b_i)-\mu}{\sigma}\right)^4 \tag{5}$$

Extreme high kurtosis signifies the presence of extreme or outlier values within the distribution. For example, in the context of healthcare data, such abnormal spikes in the vital patient parameters could include sudden elevations in blood pressure [32]. The DWT decomposed the signal arrangements into the approximation and the detail coefficients, which correspond to the low-frequency and the high-frequency parts of the data. From these coefficients, the key statistical features of mean, variance, skewness and kurtosis can be extracted, which can be used for trend analysis, abnormality detection and pattern recognition in the area of further modeling and predicting healthcare data.

3.4 Model Training

The ConvLSTM model trains on the extracted features, combining the convolutional layers to abstract spatial patterns from the inputs, while LSTMs capture the temporal dependencies in the dynamical system where this model is built. The architecture is a hybrid sequencing data such as time series collected from wearable sensors and learning complex patterns in spatially and temporally extended dimensions. The model commences the training by applying backpropagation with an increase or decrease in weights through the optimization techniques such as gradient descent. Fine-tuning adjusts hyperparameters that improve performance, such as the number of layers, learning rates and batch size [33]. The training phase consists of evaluating performance on validation data to design a model that fits and generalizes well to classify health data for normal and abnormal diagnoses. Once ready, it can be deployed in the cloud.

ConvLSTM combines the power of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, making it suitable for processing sequential data with spatial dependencies, such as time-series data from medical sensors or images [34]. It captures both the spatial patterns (through convolution) and temporal dependencies (through LSTM).

Input Gate (i_t) is expressed as equation (6),

$$i_t = \sigma(W_i * x_t + U_i * h_{t-1} + b_i) \tag{6}$$

where, σ is the sigmoid activation function. W_i and U_i are the convolutional filters applied to the input x_t and previous hidden state h_{t-1}, respectively. This gate controls how much of the new information should be added to the cell state.

Forget Gate (f_t) is represented as equation (7),

$$f_t = \sigma\left(W_f * x_t + U_f * h_{t-1} + b_f\right) \tag{7}$$

where, this gate decides what proportion of the previous cell state C_{t-1} should be forgotten.

Cell State (C_t) is embodied as equation (8),

$$C_t = f_t * C_{t-1} + i_t * \tanh\,(W_C * x_t + U_C * h_{t-1} + b_C) \tag{8}$$

where, C_t is the updated cell state, which carries long-term memory. f_t forgets parts of the previous cell state C_{t-1}, while i_t adds new information to the cell state.

Output Gate (o_t) is represented as equation (9),

$$o_t = \sigma(W_o * x_t + U_o * h_{t-1} + b_o)* \tag{9}$$

where, this gate determines the output based on the current cell state and previous hidden state. Vijai Anand Ramar et al. (2018) [35] demonstrate cloud-powered GAN integration for medical image classification. Transformed by this foundation, the proposed approach implements adaptable deep learning and attribute extraction to enhance healthcare risk prediction infrastructure.

Hidden State (h_t) is expressed as equation (10),

$$h_t = o_t * \tanh\,(C_t) \tag{10}$$

Here, the hidden state h_t will get the output of the ConvLSTM cell, which is used for the next time step as input and for prediction. In this case, the forget, input and output gates govern the flow of information and allow the model to remember or forget information at each time step, representing an essential characteristic of modeling sequences with variable time dependencies. This model can best learn such sequential data embedded with different spatial information over time, for example, in ECG signals, heart rate variability or several multivariate sensor data formats.

3.5 Deploying Models in Cloud

Upon completion of the model training phase, the next critical step involves the deployment of the trained ConvLSTM model within a cloud computing environment. This enables the healthcare monitoring system to operate in a dynamic, scalable, and accessible manner. The deployment architecture is designed to support real-time interactions with external systems, ensuring that predictions can be seamlessly integrated into ongoing healthcare workflows [36]. To facilitate interaction with the deployed model, an Application Programming Interface (API) is established. This API acts as the gateway through which external healthcare systems, IoT-enabled wearable devices, or mobile health applications can transmit patient data to the cloud-hosted model. Once data is received, the model processes the input and promptly returns predictions regarding the patient's health condition—such as identifying whether the state is normal or indicative of potential abnormality. The API ensures interoperability, enabling a wide range of health information systems to communicate effortlessly with the prediction engine.

The deployment architecture supports continuous health monitoring by providing 24/7 availability, thereby enabling real-time assessment and early intervention. Additionally, performance monitoring mechanisms are embedded within the deployment infrastructure to track metrics such as latency, prediction accuracy, and system uptime. These insights help assess the model's reliability in practical applications and identify opportunities for improvement.

One of the key advantages of cloud deployment is its scalability. The infrastructure can handle increasing volumes of health data generated by numerous users and devices without compromising performance. Furthermore, security protocols are enforced to ensure data privacy and compliance with healthcare regulations such as HIPAA or GDPR. This includes the use of encryption, secure authentication mechanisms, and access controls to protect sensitive patient data.

Moreover, the cloud-based setting enables continuous model updates and retraining. As new health data becomes available, the system can periodically update the ConvLSTM model to refine its predictive capabilities, thus maintaining high accuracy and relevance over time [37]. This adaptive learning mechanism ensures that the model evolves with changing data patterns and remains effective in diverse and dynamic healthcare environments.

4 RESULTS

The Results section highlights the comprehensive performance assessment of the proposed healthcare monitoring system, focusing on both the predictive capabilities of the model and its deployment efficiency in a cloud environment. The evaluation is carried out using a set of standard performance metrics that are widely recognized in the healthcare and machine learning domains. The integration of AI-powered bug detection and automated testing in Visrutatma Rao Vallu et al. (2023) [38] steered proposed framework toward proactive error handling, extensibility, and ensuring seamless user interaction within cloud-based healthcare platforms. The ConvLSTM model is rigorously evaluated for its ability to accurately classify patient health conditions as either normal or abnormal. Key performance indicators include accuracy, sensitivity (recall), specificity, precision, F1-score, and negative predictive value (NPV). These metrics offer a well-rounded view of the model's predictive strength, particularly its ability to correctly identify abnormal health conditions (true positives) while minimizing false alarms.

The results demonstrate that the model achieves high accuracy, indicating robust classification performance across diverse patient data. The sensitivity score highlights the model's capability to detect health anomalies effectively, which is critical in early diagnosis and intervention. In addition, the specificity and precision values confirm that the model maintains a low rate of false positives, ensuring that healthy individuals are not misclassified as abnormal [39]. Beyond model accuracy, system-level performance is also analysed. The deployment of the model in a cloud-based infrastructure is evaluated in terms of latency, uptime, and throughput. The latency results confirm that the system can deliver rapid predictions, making it suitable for time-sensitive healthcare applications. The system also demonstrates high availability and responsiveness, ensuring consistent performance under varying data loads and network conditions [40].

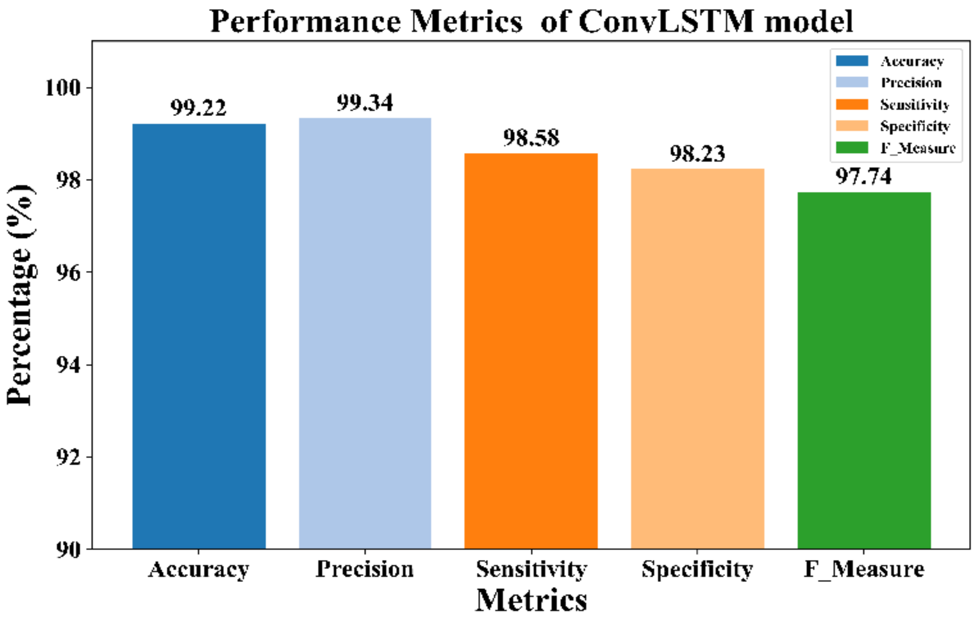

Figure 2: Performance metrics of ConvLSTM model

The detailed performance evaluation of the proposed ConvLSTM-based healthcare monitoring model is illustrated in Figure 2, showcasing its effectiveness in accurately classifying patient health conditions. The model demonstrates remarkably high accuracy, achieving a score of 99.22%, which indicates its strong ability to distinguish between normal and abnormal health patterns within the dataset. This level of accuracy reflects a highly reliable classification process, essential for real-world healthcare applications where diagnostic precision is critical [41]. The precision of the model stands at 99.34%, suggesting that nearly all instances identified as abnormal by the model are indeed true positives. This low false positive rate is vital in clinical settings to avoid unnecessary alerts or interventions, thereby optimizing healthcare resource utilization. The ways in which AI and data analytics skills boost dynamic organizational strengths and propel competitive performance is highlighted by Karthikeyan Parthasarathy (2024) [42]. In order to improve healthcare monitoring architecture, this focused attention on utilizing organizational culture, human capabilities, and data quality in the proposed framework.

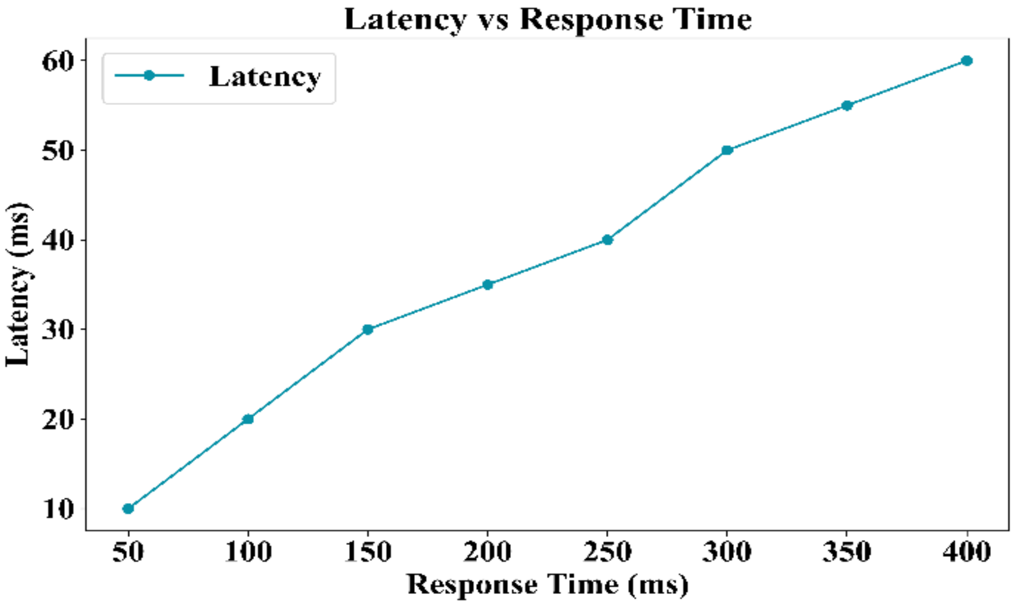

Figure 3: Latency vs Response Time for API

Figure 3 illustrates the correlation between latency and response time in the deployed healthcare monitoring system. The graph reveals a positive linear relationship between the two parameters—indicating that as the response time increases, latency also rises proportionally [43]. This relationship is particularly important in the context of cloud-based health monitoring systems where responsiveness is critical for timely diagnostics and decision-making.

5 CONCLUSIONS

This study presents a robust and scalable cloud-based healthcare monitoring system that leverages the ConvLSTM deep learning model to accurately predict and classify health conditions based on continuous data collected from wearable IoT devices and electronic medical records [44]. The model demonstrated exceptional performance, achieving 99.22% accuracy, 99.34% precision, 98.58% sensitivity, 98.23% specificity, and an F-Measure of 97.74%. In addition to its predictive accuracy, the system maintained low latency values—ranging from 10 ms to 60 ms—even as response times increased, ensuring timely diagnostics and real-time health tracking. These results confirm the system's capability to deliver efficient, accurate, and responsive healthcare support, making it a viable solution for continuous patient monitoring and early abnormality detection. Koteswararao Dondapati et al. (2021) [45] present a robust multi-criteria decision framework combining PROMETHEE, Fuzzy-AHP, and SLA analysis for hybrid optimization in cloud-based healthcare monitoring. Driven forward by this, the proposed method integrates similar techniques to advance healthcare network optimization.

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