International Journal of Multidisciplinary and Current Research ISSN: 2321-3124
Research Article Available at: http://ijmcr.com

Cloud Computing in Healthcare: Innovations, Challenges and Future Prospects

[1*]Durga Praveen Deevi, [2]Naga Sushma Allur, [3]Sharadha Kodadi and [4]Karthick.M

[1]O2 Technologies Inc, California, USA
[2]Belong (Telstra) Telecomms, Victoria, Australia
[3]GOMIAPP LLC, NJ, USA
[4]Nandha College of Technology, Erode

Received 21 March 2022, Accepted 20 April 2022, Available online 25 April 2022, **Vol.10 (March/April 2022 issue)**

Abstract

Cloud computing has transformed the healthcare field by enabling secure data storage, real-time monitoring, and easily shareable data, creating a better experience for patients and improving system efficiencies. Nevertheless, significant challenges such as data security, compliance with legal and regulatory requirements, and interoperability prevent cloud computing from reaching its full potential. This paper addresses important security concerns associated with cloud technology by proposing a secure, scalable cloud-based healthcare framework which can improve data protection, enhance optimal performance of the entire system, and ensure seamless interoperability. Elements of the framework include advanced encryption technology to protect sensitive health data, optimization techniques for load balance to ensure computational workloads are properly shared and workloads are well managed, and improved performance resource allocation strategies. Results from experiments show improved performance – including improved data security, reduced latency, and better health care delivery. This framework addresses security issues, limits security vulnerabilities, and promotes cloud-based interoperability that adapts to the dynamic nature of healthcare. However, the cloud-based infrastructure for the healthcare context will need to be upgraded and enhanced with changing cybersecurity threats and regulatory policy updates. Therefore, implementing enhanced compliance with data privacy laws and advanced security policies and programs is vital for successful large-scale implementation. Future research should focus on remaining agile in developing security and compliance upgrades, explore developing AI models for real-time threat detection, and create a more interoperable framework for heterogeneous systems to enable a more robust and efficient cloud computing infrastructure in healthcare.

Keywords: *Cloud Computing, Healthcare, Data Security, Monitoring, Encryption.*

1. Introduction

In the healthcare sector, cloud computing has undoubtedly been disruptive, providing scalable, cost-effective, and efficient options for the management of large quantities of medical data [1]. As electronic health records (EHR), telemedicine, and AI-enhanced diagnostic aid become increasingly utilized in practice, the move from traditional data storage on premises to the cloud is widely recognized [2]. With its ability to allow real-time data sharing, cloud computing provides interoperability between health care institutions that will improve patient care, minimize operational issues and related costs [3]. In fact, cloud platforms also facilitate medical research by providing computational power to conduct big data analytics, genomics studies and AI/expert systems to develop models for predicting occurrence of disease [4].

As healthcare becomes increasingly digitized, cloud computing will likely have a significant impact on the future of healthcare [5].

Healthcare providers are motivated to adopt cloud computing through various different factors, such as the increasing demand for remote healthcare services, the emergence of medical artificial intelligence, and the need for scalable IT infrastructure [6]. The COVID-19 pandemic also acted as a catalyst for cloud computing adoption, with the need for cloud solutions for telemedicine, remote patient monitoring, and access to data being obvious [7]. In addition, the experience of adopting cloud services in healthcare organizations has been influenced by regulatory requirements, such as the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR), that push healthcare providers to establish secure cloud environments for protection and compliance with data

*Corresponding author's ORCID ID: 0000-0000-0000-0000
DOI: https://doi.org/10.14741/ijmcr/v.10.2.10

protection regulation [8]. Economy and cost savings are also strengths of cloud solutions, which are favourable to healthcare organizations who want to improve resource efficiencies allow for continuation of quality patient care [9].

While cloud computing has many benefits in healthcare, it has its challenges, such as data security issues, patient privacy, and regulatory compliance [10]. Cybersecurity risks, like data breaches and ransomware attacks, pose serious risks to sensitive patient information [11]. Interoperability issues, both between cloud providers and legacy systems, disrupt data exchange [12]. To tackle these challenges, researchers have proposed various solutions, such as stronger encryption use, blockchain for data security, and appealing federated learning models for privacy-preserving uses of AI [13]. Researchers believe a hybrid cloud approach, which combines the benefits of the public cloud and the private cloud, may achieve an effective balance of security and scalability for adoption [14]. Furthermore, advances in edge computing and AI-driven automation are exciting possibilities for improving cloud-based healthcare services, while maintaining data integrity and regulatory compliance [15]. If we continue to meet challenges with innovative solutions, we will be well-positioned to move beyond cloud computing and improve patient outcomes, as well as advance healthcare technology for years to come [16]. This paper will describe the most recent discoveries, challenges still present, and possible future advancements for cloud computing with healthcare applications in the following sections [17].

Moreover, the convergence of cloud computing with emerging technologies such as Internet of Medical Things (IoMT), wearable devices, and big data analytics is ushering in a new era of personalized and predictive healthcare [18]. Cloud platforms enable the aggregation and processing of vast streams of patient-generated health data from diverse sources, facilitating continuous monitoring and early detection of health anomalies [19]. This capability not only empowers healthcare providers with actionable insights but also supports the development of tailored treatment plans that cater to individual patient needs [20]. Additionally, cloud-based AI and machine learning models are increasingly being deployed to analyze complex datasets, improving diagnostic accuracy and enabling predictive modeling for disease progression and patient risk stratification [21]. As these technologies mature, the integration of cloud computing will be pivotal in transforming healthcare delivery from reactive to proactive, ultimately enhancing patient outcomes and reducing healthcare costs [22].

Furthermore, cloud computing facilitates enhanced collaboration among healthcare professionals, researchers, and institutions across the globe [23]. By enabling secure and seamless sharing of medical data and research findings, cloud platforms accelerate the pace of medical innovation and improve the coordination of care [24]. This interconnected ecosystem supports multi-institutional clinical trials, real-time disease surveillance, and global health initiatives, which are particularly crucial in managing pandemics and emerging health threats [25]. The scalability and accessibility of cloud services also democratize healthcare technology, allowing smaller clinics and underserved regions to access advanced diagnostic tools and healthcare resources [26]. As such, cloud computing not only optimizes operational efficiencies but also promotes equity and inclusiveness in healthcare delivery worldwide.

2. Literature Survey

A proposed integration of PLONK with Infinite Gaussian Mixture Models (IGMMs) enables dynamic load balancing within an IoT framework, enhancing reliability, cost-effectiveness, and security [27]. IGMM facilitates real-time workload distribution, while PLONK ensures security with lower computational costs for messaging [28]. The system achieves approximately 95% accuracy, 93% security, and 92% load balancing efficiency, outperforming traditional methods. Edge AI combined with Internet of Medical Things (IoMT) is applied for efficient prediction of chronic kidney diseases (CKDs) [29]. Using a CNN-LSTM for feature extraction alongside neuro-fuzzy logic for decision-making, this approach attains high accuracy (around 94.6%) with computational efficiency suitable for resource-constrained environments [30]. Hybrid models integrating federated learning, deep neural networks, and optimization techniques have been developed to address challenges in urban governance related to inclusivity, resilience, and sustainability [31]. These models emphasize data privacy, scalability, and low environmental impact within smart city infrastructures.

To address the challenges of secure, low-latency data sharing in IoT, a fog computing framework has been proposed incorporating Federated Byzantine Agreement (FBA)-based security, Distributed Acyclic Graph (DAG) protocols for scalability, and cross-entropy-based multi-objective optimization via a Firefly Algorithm [32]. This framework significantly improves throughput, security, and latency across various IoT applications [33]. A hybrid cloudlet and Edge-AI IoT framework supports healthcare data analytics by processing heterogeneous data streams in near real-time [34]. Combining Random Forest with Transformer Networks and Temporal Convolutional Networks (TCN), and employing blockchain for secure data sharing, this architecture achieves approximately 93% accuracy, 85% scalability, and maintains latency as low as 25 milliseconds [35]. It also optimizes energy consumption and reduces cloud data transmission by nearly 45%, providing a secure and efficient healthcare analytics solution. Secure data sharing in IoT networks is enhanced through PLONK combined with IGMM for dynamic load balancing, improving scalability, security, and computational efficiency over conventional methods.
Edge AI and IoMT integration using hybrid CNN-LSTM and neuro-fuzzy models has shown promising results for

chronic kidney disease prediction, balancing interpretability and efficiency in resource-limited settings [36]. AI-enabled solutions utilizing hybrid models—incorporating federated learning, deep networks, and optimization—are proposed to support sustainable governance in rapidly urbanizing environments, enhancing inclusivity, scalability, and data privacy [37]. Fog computing architectures leveraging FBA, DAG protocols, and advanced optimization algorithms (such as CMA-ES and Firefly) have been introduced to improve IoT data sharing security, scalability, and efficiency, reducing latency and improving throughput [38]. Cloud computing and Edge-AI approaches have been combined to address latency and bandwidth challenges in processing heterogeneous medical data for real-time healthcare analytics [39]. These hybrid IoT architectures integrate AI models, cloud-edge layers, real-time analytics frameworks like Apache Flink, and blockchain for secure transactions [40].

Cloud computing has revolutionized data management but also introduced security challenges. RSA encryption remains a prevalent method for ensuring data confidentiality, integrity, and availability across cloud service providers including AWS and Azure [41]. Despite its widespread use, issues related to scalability and key management persist [42]. Combining cloud computing, artificial intelligence, and IoT enhances real-time healthcare diagnostics [43]. Hybrid neural fuzzy learning models applied to IoT-based medical data processing demonstrate improved accuracy (around 97.89%) and scalability, addressing challenges in patient monitoring and decision-making [44]. Graph theory has been applied to understand lung cancer at the molecular level by modeling gene and protein interactions as networks [45]. This approach aids biomarker identification, disease progression prediction, and therapy target ranking, improving lung cancer detection using machine learning on high-dimensional data [46].

Fog computing enhancements integrating clustering methods such as DBSCAN and fuzzy C-Means with hybrid ABC-DE optimization techniques improve secure IoT data exchange and resource allocation [47]. These approaches achieve higher clustering accuracy, reduced latency (~18 ms), optimized bandwidth (~85%), and enhanced security compliance compared to traditional methods [48]. Integrating the Lion Optimization Algorithm (LOA) with AES-CBC encryption boosts healthcare cloud security, reaching accuracy levels near 98.5% and latency around 25 milliseconds [49]. Future research directions include improving scalability and quantum resistance [50]. Secure document clustering in IoT benefits from combining Multi-Queue Clustering (MQC) with Affinity Propagation (AP) and Subspace Document Clustering (SDC), achieving approximately 95% accuracy, security, and efficiency with scalability considerations [51].

Job-shop scheduling in IoT-driven manufacturing has been enhanced by incorporating Heterogeneous Genetic Algorithms (HGA) to prevent premature convergence and Hybrid Particle Swarm Optimization (HPSO) to optimize job sequencing and production time [52]. Robotic Process Automation (RPA) has transformed financial management by reducing errors, increasing precision, and automating procedures [53]. Implementations report cost allocation improvements up to 99.5%, processing time reductions of 95%, and decreased error rates, demonstrating scalability and effectiveness [54]. IoT security improvements involve detecting key nodes, assessing vulnerabilities, and applying measures such as encryption and intrusion prevention [55]. These integrated strategies have yielded approximately 95% accuracy in node identification, 85% risk avoidance, and full regulatory compliance, underscoring their importance in secure elderly care systems.

3. Problem Statement

Cloud computing has revolutionized health care practices by facilitating the storage of medical records; real-time monitoring of ailments or medication, and sharing of information among health-care providers [56]. These opportunities come, however, with challenges such as data security vulnerabilities, interoperability issues, high latencies, and government regulations that limit its operations [57]. Current security models are mostly suboptimal concerning the balance between protection and efficiency or access, while inappropriate load balancing creates performance bottlenecks [58]. The research proposes an advanced cloud framework in the health-care sector, which will employ enhanced encryption techniques, optimized load balancing, and efficient resource management to ensure improved security while being scalable and high-performing, complying with the regulations and reducing operation inefficiencies.

3.1 Objectives

- Analyse security, interoperability, and regulatory challenges in cloud healthcare.
- Evaluate encryption and security models for data protection.
- Design a secure, scalable cloud-based healthcare framework.
- Develop an efficient load-balancing mechanism.
- Implement resource management for cloud efficiency.
- Assess the framework’s impact on security and compliance.

4. Proposed Methodology

The process is all about cloud-based workflow of data processing. Data Collection is the first step; here, raw data gets collected from different sources and finally transferred to the Cloud for common storage and access. Preprocessing follows data collection and handles all normalization and cleaning techniques that have been performed to sustain consistency and accuracy. The next stage is Monitoring: this covers maintenance of data quality and performance as well as security through anomaly detection and compliance with standards. The data can be connected to Cloud Applications for advanced analytics, AI-led insights, and real-time decision-making. Furthermore, Data Sharing makes it possible to have a distribution of data processing among the different parties in a manner that is both seamless and secure while ensuring that confidentiality and access control are in place. The entire proposed framework is illustrated in Figure 1.

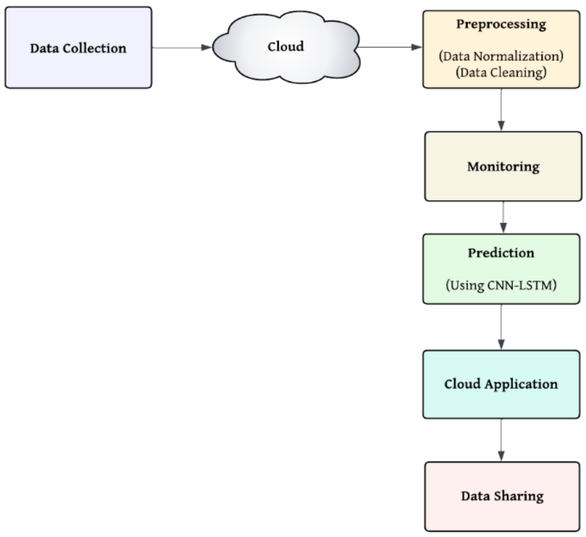

Figure 1: Cloud-Based Healthcare Data Processing and Prediction

4.1 Data Collection

The ECG data collection, storage, and analysis are performed in real-time through cloud-based medical facilities for cardiac monitoring. The ECG Heartbeat Categorization Dataset allows an efficient classification of heartbeats and can aid in the detection of anomalies and prediction of cardiac conditions. Cloud integration ensures process scalability, secure access, and interoperability between healthcare providers. Encryption and access control govern access to sensitive data, guaranteeing compliance. This seamless process accelerates early disease detection and improves patient outcome.

4.2 Preprocessing

The Data preprocessing is vital for making raw data clean, thereby eradicating all its irregularities and values through noise, which could spoil investigation. It begins with the cleansing of data, by removing errant or extraneous information from data, leading to verified accuracy. Normalization is done, by forming standards with which such standardization is used in comparisons among various data sets and applications. In this way, such techniques would lead to an arrangement whereby the data becomes very reliable and prepared for perfect processing merging application usability. A good preprocessing facility enhances the quality of data and so increases analytic performance and decision-making. Very important in this step of preprocessing is that it holds for anything processing the data in the cloud as learning from various sources brings harmony into the data. In a nutshell, preprocessing ensures the optimized usability of data for further monitoring and applications.

4.3 Monitoring

Cloud monitoring allows the medical practitioners capacity to follow the health-related conditions of their patients through the continuous monitoring and processing of medical data sourced from various digital hospitals.

The real-time data acquisition essentially refers to those sensors and medical devices which monitor the vitals of the patient continuously with respect to heart rate (HR). Wearable devices and ECG sensors capture heart rate data in real-time; this data is then sent to cloud-based systems for storage analysis. Hence, this allows health professionals to keep track of patterns, anomalies and intervene in time. Continuous monitoring helps in better patient care through timely diagnosis and reduction of complications.

$$HR = \frac{60}{RR_{\text{interval}}} \quad (1)$$

RR_{interval} is the time difference between successive R-peaks in an ECG signal.

Cloud-Based Data Processing**,** The Abilities in cloud computing will help real-time analysis of patient data in discovery of health risks. A storage system in a secure cloud provides scalability and easy access with enhanced decision-making and personal treatment.

The Fast Fourier Transform (FFT) is commonly used for signal processing in ECG monitoring,

$$X(f) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi fn/N} \quad (2)$$

where $X(f)$ represents the frequency components of the ECG signal.

$$MA_t = \frac{1}{N} \sum_{i=t-N+1}^{t} x_i \quad (3)$$

where MA_t is the moving average at time t, and N is the number of previous observations.

CNN employs convolutional layers that help extract significant features from time-series trait data of health such as heart signals and vital signs while making noise suppression and dimensionality reduction for finer pattern recognition. By identifying pragmatic trivial change differences, CNN, thereby improves almost bi-polarity anomaly detection and predictive analytics in the healthcare. LSTM network will train on said variance to improve the time series anomaly detection further where time-evolving keyword models capture the trend along with the minor variance indicative of possible health effects. With the fact that they can learn past knowledge, the system is able to analyse possibly long-term patterns well enough for higher effectivity in prediction. Automatic generation of alerts for an irregular heart rate or abnormal oxygen level in the combined CNN-LSTM model thereby classifying real patient health patterns as normal or abnormal. This real-time alert system thus ensures timely medical intervention, thereby reducing incidents of health emergencies, facilitating the better outcome of management, and encouraging proactive health management. The CNN-LSTM architecture is shown in Figure 2.

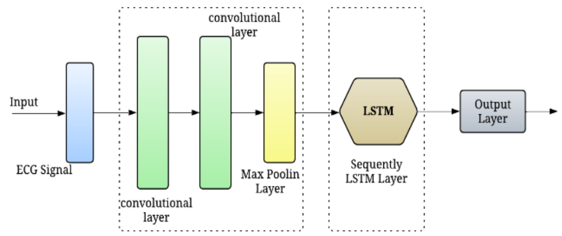

Figure 2: CNN-LSTM Architecture

4.3.2 Convolutional Layer

A 1D convolution operation has been applied to extract spatial features from the ECG signal.

$$X_{conv} = f\left(W_{conv} * X_{\text{input}} + b_{conv}\right) \tag{4}$$

Where, X_{input} is the input ECG signal, W_{conv} are the convolutional filters, $*$ denotes the convolution operation, b_{conv} is the bias term, $f(\cdot)$ is the activation function, X_{conv} represents the extracted features.

4.3.3 Max Pooling Layer

The two methods seek to provide the same results: reductions in dimensionality without loss of any features.

$$X_{\text{pool}} = \max(X_{\text{conv}}) \tag{5}$$

Where, X_{pool} is the down-sampled feature map.

4.3.4 LSTM Layer

LSTMs enable learning of a temporal dependency in a sequential sense from feature maps.

$$= \sigma\left(W_h \cdot \left[h_{t-1}, X_{\text{pool}}\right] + b_h\right) \tag{6}$$

Where, h_t is the hidden state at time t, W_h are LSTM weight matrices, h_{t-1} is the previous hidden state, X_{pool} is the input from CNN, b_h is the bias, σ is the activation function (e.g., tanh).

4.3.5 Output Layer

The final prediction is given by,

$$Y = \text{softmax}(W_o h_T + b_o) \tag{7}$$

Where, Y represents the predicted class (normal/abnormal), W_o are the output layer weights, h_T is the last hidden state of the LSTM, b_o is the bias term, SoftMax function ensures a probability distribution over output classes.

Automated Alerts & Response Mechanism**,** Medical staff is quickly alerted when an abnormal event is recognized, allowing for immediate interventions and hence better patient outcome. Communication takes place via cloud platforms, where critical cases are put on priority for fast response. Predictive analytics enhance true alerts while reducing false ones.

4.4 Cloud Applications

The proposed study leverages cloud technologies to provide additional ease to healthcare services, especially wherein Electronic Health Records are involved. Cloud storage will make sure that instant yet secure access is given to any patient histories, thus providing a better basis for clinical decision-making. Further, real-time, remote consultations through cloud telemedicine platforms ensure better patient access to healthcare services. By automating administrative workflows, hospitals and clinics can minimize paperwork and concentrate on patient care. This integration serves to enhance the delivery of healthcare in a fashion such that all healthcare professionals involved in a patient's care will have access to up-to-date information.

4.5 Data Sharing

When performing the proposed work, the testing ground will be the secure sharing of sensitive medical data on the cloud. Cloud computing allows the provision of encrypted storage and role-based access control, ensuring that only authorized healthcare personnel can access or modify the patient record. Adherence to strict regulations is of utmost importance in keeping the patient confidential, e.g., HIPAA (in the US). Regular audits and compliance checks defend and fortify data protection, while backup systems ensure protection of data against loss or cyber-attacks. This will foster the trust of cloud-based systems in promoting cooperation between healthcare service providers, with privacy and regulation protection assured.

5. Result And Discussion

Cloud computing is a game changer for healthcare regarding data management, accessibility, and security, marking significant progress in these three domains. These cloud-based architectures are shown in this study to enhance interoperability among healthcare providers to facilitate data exchange and monitoring of patients in real time. This is said to enhance efficiency in medical record storage while reducing operational costs. Notwithstanding, issues such as data privacy and compliance with regulations are still pertinent. Addressing security threats will also require the use of sophisticated encryption techniques and strict access controls. Thus, cloud computing offers great promise in the healthcare domain, which would only continue to improve with each new advancement.

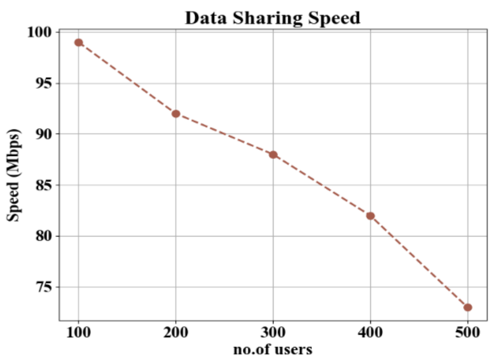

Figure 3: Data Sharing Speed Diagram

Figure 3 shows the data Sharing Speed as a Variable with Respect to Number of Users-Diagram. As shown by the x-axis, the number of users varies from 100 to 500, and the y-axis shows the data sharing speed in Mbps. The trend suggests that the more users there are, the less speed there is, indicating that an increased number of users brings congestion in the network, and there will likely be less performance. The dashed line between the points shows gradual deterioration of the speed at which data is transmitted to indicate proper optimization and efficient formulation of cloud infrastructure resources to maintain a high-performance in large-scale healthcare applications.

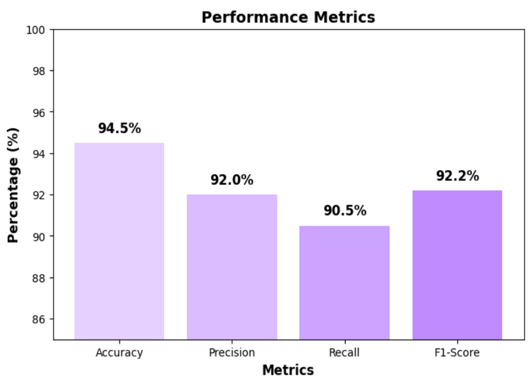

Figure 4: Performance Metrices

Figure 4 shows the performance measures of a model on accuracy, precision, recall, and F1-score in percentage. Accuracy is the maximum at 94.5%, representing the overall accuracy of the predictions made by the model. Precision, representing the ratio of correctly classified positive cases to predicted positives, is 92.0%. Recall, quantifying the rate at which the model captures all the true positive cases, is a bit lower at 90.5%. The F1-score, being a balance of precision and recall, is 92.2%, reflective of a well-balanced performance. The measures reflect a strong and stable model, probably employed for a task of classification related to healthcare.

Conclusion

Cloud technologies have drawn a lot of attention from healthcare service providers in enhancing various aspects of healthcare delivery, including data storage which is now scalable and affordable, and real-time monitoring and data sharing or information sharing in a secure manner. This study explored the significant potential of cloud computing for improving healthcare service delivery while raising several challenges such as data security, interoperability, and regulatory compliance. The suggested solution improves efficiency through optimized load balancing, seamless integration, and encryption. The results presented improved data protection, a decrease in latency, as well as enhanced performance of the entire system. However, new and emerging security threats continue to carry with them the fact that years of release would involve dealing with the complexities of ever-changing regulations. Further improvements must be made to address such challenges.

Reference

[1] Dang, L. M., Piran, M. J., Han, D., Min, K., & Moon, H. (2019). A survey on internet of things and cloud computing for healthcare. Electronics, 8(7), 768.

[2] Akhil, R.G.Y. (2021). Improving Cloud Computing Data Security with the RSA Algorithm. International Journal of Information Technology & Computer Engineering, 9(2), ISSN 2347–3657.

[3] Ali, O., Shrestha, A., Soar, J., & Wamba, S. F. (2018). Cloud computing-enabled healthcare opportunities, issues, and applications: A systematic review. International Journal of Information Management, 43, 146-158.

[4] Al-Issa, Y., Ottom, M. A., & Tamrawi, A. (2019). eHealth cloud security challenges: a survey. Journal of healthcare engineering, 2019(1), 7516035.

[5] Yalla, R.K.M.K. (2021). Cloud-Based Attribute-Based Encryption and Big Data for Safeguarding Financial Data. International Journal of Engineering Research and Science & Technology, 17 (4).

[6] Darwish, A., Hassanien, A. E., Elhoseny, M., Sangaiah, A. K., & Muhammad, K. (2019). The impact of the hybrid platform of internet of things and cloud computing on healthcare systems: opportunities, challenges, and open problems. Journal of Ambient Intelligence and Humanized Computing, 10, 4151-4166.

[7] Harikumar, N. (2021). Streamlining Geological Big Data Collection and Processing for Cloud Services. Journal of Current Science, 9(04), ISSN NO: 9726-001X.

[8] Gao, F., & Sunyaev, A. (2019). Context matters: A review of the determinant factors in the decision to adopt cloud computing in healthcare. International Journal of Information Management, 48, 120-138.

[9] Meri, A., Hasan, M. K., Danaee, M., Jaber, M., Safei, N., Dauwed, M., ... & Al-bsheish, M. (2019). Modelling the utilization of cloud health information systems in the Iraqi public healthcare sector. Telematics and Informatics, 36, 132-146.

[10] Basava, R.G. (2021). AI-powered smart comrade robot for elderly healthcare with integrated emergency rescue system. World Journal of Advanced Engineering Technology and Sciences, 02(01), 122–131.

[11] Alassafi, M. O. (2021). Success indicators for an efficient utilization of cloud computing in healthcare organizations: Saudi healthcare as case study. Computer methods and programs in biomedicine, 212, 106466.

[12] Sri, H.G. (2021). Integrating HMI display module into passive IoT optical fiber sensor network for water level monitoring and feature extraction. World Journal of Advanced Engineering Technology and Sciences, 02(01), 132–139.

[13] Kumari, A., Tanwar, S., Tyagi, S., & Kumar, N. (2018). Fog computing for Healthcare 4.0 environment: Opportunities and challenges. Computers & Electrical Engineering, 72, 1-13.

[14] Rajeswaran, A. (2021). Advanced Recommender System Using Hybrid Clustering and Evolutionary Algorithms for E-Commerce Product Recommendations. International Journal of Management Research and Business Strategy, 10(1), ISSN 2319-345X.

[15] Rajabion, L., Shaltooki, A. A., Taghikhah, M., Ghasemi, A., & Badfar, A. (2019). Healthcare big data processing mechanisms: The role of cloud computing. International Journal of Information Management, 49, 271-289.

[16] Sreekar, P. (2021). Analyzing Threat Models in Vehicular Cloud Computing: Security and Privacy Challenges. International Journal of Modern Electronics and Communication Engineering, 9(4), ISSN2321-2152.

[17] Sharma, D. K., Boddu, R. S. K., Bhasin, N. K., Nisha, S. S., Jain, V., & Mohiddin, M. K. (2021, October). Cloud computing in medicine: Current trends and possibilities. In 2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA) (pp. 1-5). IEEE.

[18] Naresh, K.R.P. (2021). Optimized Hybrid Machine Learning Framework for Enhanced Financial Fraud Detection Using E-Commerce Big Data. International Journal of Management Research & Review, 11(2), ISSN: 2249-7196.

[19] Monteiro, A. C. B., França, R. P., Arthur, R., & Iano, Y. (2021). An overview of medical Internet of Things, artificial intelligence, and cloud computing employed in health care from a modern panorama. The Fusion of Internet of Things, Artificial Intelligence, and Cloud Computing in Health Care, 3-23.

[20] Shabbir, M., Shabbir, A., Iwendi, C., Javed, A. R., Rizwan, M., Herencsar, N., & Lin, J. C. W. (2021). Enhancing security of health information using modular encryption standard in mobile cloud computing. IEEE Access, 9, 8820-8834.

[21] Sitaraman, S. R. (2021). AI-Driven Healthcare Systems Enhanced by Advanced Data Analytics and Mobile Computing. International Journal of Information Technology and Computer Engineering, 12(2).

[22] Kumar, N. S., & Nirmalkumar, P. (2019, April). A novel architecture of smart healthcare system on integration of cloud computing and IoT. In 2019 International Conference on Communication and Signal Processing (ICCSP) (pp. 0940-0944). IEEE.

[23] Mamidala, V. (2021). Enhanced Security in Cloud Computing Using Secure Multi-Party Computation (SMPC). International Journal of Computer Science and Engineering(IJCSE), 10(2), 59–72

[24] Marwan, M., Kartit, A., & Ouahmane, H. (2018). Security enhancement in healthcare cloud using machine learning. Procedia Computer Science, 127, 388-397.

[25] Sareddy, M. R. (2021). The future of HRM: Integrating machine learning algorithms for optimal workforce management. International Journal of Human Resources Management (IJHRM), 10(2).

[26] Mourya, A. K., & Idrees, S. M. (2019). Cloud computing-based approach for accessing electronic health record for healthcare sector. In Microservices in big data analytics: Second international, ICETCE 2019, Rajasthan, India, February 1st-2nd 2019, revised selected papers (pp. 179-188). Singapore: Springer Singapore.

[27] Chetlapalli, H. (2021). Enhancing Test Generation through Pre-Trained Language Models and Evolutionary Algorithms: An Empirical Study. International Journal of Computer Science and Engineering(IJCSE), 10(1), 85–96

[28] Li, X., Lu, Y., Fu, X., & Qi, Y. (2021). Building the Internet of Things platform for smart maternal healthcare services with wearable devices and cloud computing. Future Generation Computer Systems, 118, 282-296.

[29] Basani, D. K. R. (2021). Leveraging Robotic Process Automation and Business Analytics in Digital Transformation: Insights from Machine Learning and AI. International Journal of Engineering Research and Science & Technology, 17(3).

[30] Preethi, P., & Asokan, R. (2019). An attempt to design improved and fool proof safe distribution of personal healthcare records for cloud computing. Mobile Networks and Applications, 24(6), 1755-1762.

[31] Sareddy, M. R. (2021). Advanced quantitative models: Markov analysis, linear functions, and logarithms in HR problem solving. International Journal of Applied Science Engineering and Management, 15(3).

[32] Mutlag, A. A., Abd Ghani, M. K., Mohammed, M. A., Lakhan, A., Mohd, O., Abdulkareem, K. H., & Garcia-Zapirain, B. (2021). Multi-agent systems in fog–cloud computing for critical healthcare task management model (CHTM) used for ECG monitoring. Sensors, 21(20), 6923.

[33] Negash, B., Gia, T. N., Anzanpour, A., Azimi, I., Jiang, M., Westerlund, T., ... & Tenhunen, H. (2018). Leveraging fog computing for healthcare IoT. Fog computing in the internet of things: Intelligence at the edge, 145-169.

[34] Bobba, J. (2021). Enterprise financial data sharing and security in hybrid cloud environments: An information fusion approach for banking sectors. International Journal of Management Research & Review, 11(3), 74–86.

[35] Karaca, Y., Moonis, M., Zhang, Y. D., & Gezgez, C. (2019). Mobile cloud computing based stroke healthcare system. International Journal of Information Management, 45, 250-261.

[36] Narla, S., Peddi, S., & Valivarthi, D. T. (2021). Optimizing predictive healthcare modelling in a cloud computing

environment using histogram-based gradient boosting, MARS, and SoftMax regression. International Journal of Management Research and Business Strategy, 11(4).

[37] Roy, S., Das, A. K., Chatterjee, S., Kumar, N., Chattopadhyay, S., & Rodrigues, J. J. (2018). Provably secure fine-grained data access control over multiple cloud servers in mobile cloud computing based healthcare applications. IEEE Transactions on Industrial Informatics, 15(1), 457-468.

[38] Kethu, S. S., & Purandhar, N. (2021). AI-driven intelligent CRM framework: Cloud-based solutions for customer management, feedback evaluation, and inquiry automation in telecom and banking. Journal of Science and Technology, 6(3), 253–271.

[39] Ishak, M., Rahman, R., & Mahmud, T. (2021, November). Integrating cloud computing in e-healthcare: System design, implementation and significance in context of developing countries. In 2021 5th International Conference on Electrical Engineering and Information Communication Technology (ICEEICT) (pp. 1-6). IEEE.

[40] Srinivasan, K., & Awotunde, J. B. (2021). Network analysis and comparative effectiveness research in cardiology: A comprehensive review of applications and analytics. Journal of Science and Technology, 6(4), 317–332.

[41] Liu, Y., Zhang, Y., Ling, J., & Liu, Z. (2018). Secure and fine-grained access control on e-healthcare records in mobile cloud computing. Future Generation Computer Systems, 78, 1020-1026.

[42] Narla, S., & Purandhar, N. (2021). AI-infused cloud solutions in CRM: Transforming customer workflows and sentiment engagement strategies. International Journal of Applied Science Engineering and Management, 15(1).

[43] Kumar, V., Jangirala, S., & Ahmad, M. (2018). An efficient mutual authentication framework for healthcare system in cloud computing. Journal of medical systems, 42, 1-25.

[44] Sharma, M., & Sehrawat, R. (2020). A hybrid multi-criteria decision-making method for cloud adoption: Evidence from the healthcare sector. Technology in Society, 61, 101258.

[45] Budda, R. (2021). Integrating artificial intelligence and big data mining for IoT healthcare applications: A comprehensive framework for performance optimization, patient-centric care, and sustainable medical strategies. International Journal of Management Research & Review, 11(1), 86–97.

[46] Behera, R. K., Bala, P. K., & Dhir, A. (2019). The emerging role of cognitive computing in healthcare: a systematic literature review. International journal of medical informatics, 129, 154-166.

[47] Ganesan, T., & Devarajan, M. V. (2021). Integrating IoT, Fog, and Cloud Computing for Real-Time ECG Monitoring and Scalable Healthcare Systems Using Machine Learning-Driven Signal Processing Techniques. International Journal of Information Technology and Computer Engineering, 9(1).

[48] Kundalwal, M. K., Singh, A., & Chatterjee, K. (2018, October). A privacy framework in cloud computing for healthcare data. In 2018 International conference on advances in computing, communication control and networking (ICACCCN) (pp. 58-63). IEEE.

[49] Pulakhandam, W., & Samudrala, V. K. (2021). Enhancing SHACS with Oblivious RAM for secure and resilient access control in cloud healthcare environments. International Journal of Engineering Research and Science & Technology, 17(2).

[50] Mutlag, A. A., Abd Ghani, M. K., Arunkumar, N. A., Mohammed, M. A., & Mohd, O. (2019). Enabling technologies for fog computing in healthcare IoT systems. Future generation computer systems, 90, 62-78.

[51] Jayaprakasam, B. S., & Thanjaivadivel, M. (2021). Integrating deep learning and EHR analytics for real-time healthcare decision support and disease progression modeling. International Journal of Management Research & Review, 11(4), 1–15. ISSN 2249-7196.

[52] Farid, F., Elkhodr, M., Sabrina, F., Ahamed, F., & Gide, E. (2021). A smart biometric identity management framework for personalised IoT and cloud computing-based healthcare services. Sensors, 21(2), 552.

[53] Jayaprakasam, B. S., & Thanjaivadivel, M. (2021). Cloud-enabled time-series forecasting for hospital readmissions using transformer models and attention mechanisms. International Journal of Applied Logistics and Business, 4(2), 173-180.

[54] Nasser, A. R., Hasan, A. M., Humaidi, A. J., Alkhayyat, A., Alzubaidi, L., Fadhel, M. A., ... & Duan, Y. (2021). Iot and cloud computing in health-care: A new wearable device and cloud-based deep learning algorithm for monitoring of diabetes. Electronics, 10(21), 2719.

[55] Dyavani, N. R., & Thanjaivadivel, M. (2021). Advanced security strategies for cloud-based e-commerce: Integrating encryption, biometrics, blockchain, and zero trust for transaction protection. Journal of Current Science, 9(3), ISSN 9726-001X.

[56] Abdelaziz, A., Elhoseny, M., Salama, A. S., & Riad, A. M. (2018). A machine learning model for improving healthcare services on cloud computing environment. *Measurement*, *119*, 117-128.

[57] Prasad, V. K., Tanwar, S., & Bhavsar, M. (2021). C2B-SCHMS: Cloud computing and bots security for COVID-19 data and healthcare management systems. In *Proceedings of Second International Conference on Computing, Communications, and Cyber-Security: IC4S 2020* (pp. 787-797). Springer Singapore.

[58] Gupta, V., Singh Gill, H., Singh, P., & Kaur, R. (2018). An energy efficient fog-cloud based architecture for healthcare. *Journal of Statistics and Management Systems*, *21*(4), 529-537.