

Utilizing Hybrid Cloud Computing with Machine Learning and Deep Learning to Enhance Privacy, Security, and Empower Patients

G. Raja Ramesh ^{1*}, Rajesh E ²

^{1*} Research Scholar, School of Computing Science & Engineering, Galgotias University, Greater Noida, India.

^{1*} Email: g.21scse3010031@galgotiasuniversity.edu.in

² Professor, School of Computing Science & Engineering, Galgotias University, Greater Noida, India.

ARTICLE INFO

Received: 22 Nov 2024

Revised: 26 Dec 2024

Accepted: 10 Jan 2025

ABSTRACT

This study investigates the effectiveness of Hybrid Cloud solutions in meeting the challenges encountered within the healthcare sector. Hybrid Cloud technology provides adaptable, on-demand services that empower hospitals and clinics to sidestep costly infrastructure upgrades and streamline maintenance costs. The scalability of cloud platforms addresses the fluctuating demands of the health and wellness industry, supported by fail-safes like disaster recovery and redundancy to ensure continuous service availability. At the heart of this infrastructure lies the Hybrid Health Cloud (HHC), serving as a central data repository for efficient information access and sharing. Nevertheless, obstacles emerge due to the time-consuming decryption and memory-intensive re-encryption processes inherent in HHC schemes. To counter these challenges, a novel approach integrates machine learning, deep learning, and Hybrid Cloud technologies, aiming to enhance system efficiency. Leveraging SHA-based algorithmic perspectives such as categorization, grouping, deep semantic networks, and quantum semantic networks, this study strives to improve both prediction accuracy and data protection.

Keywords: Cloud computing, Machine Learning, Deep Learning, healthcare, secure, cryptograph.

INTRODUCTION

Worldwide healthcare systems face enormous problems from chronic illnesses including diabetes, chronic obstructive lung disease, and cardiovascular disease. The prevalence of these conditions is on the rise, with diabetes alone affecting nearly 1 in 10 adults globally, as reported by the World Health Organization (WHO). Managing chronic diseases often entails regular check-ups and monitoring, which can be costly, time-consuming, and inconvenient for patients. However, many cases of chronic diseases do not require immediate medical intervention, making it feasible to adopt proactive approaches to monitoring and managing patients' conditions [1]. The advent of information and communication technology (ICT) has paved the way for innovative e-Health solutions, particularly in the realm of home-based healthcare. By leveraging digital health devices, individuals can monitor various physiological signals and health parameters in their home environments during daily activities [2].

This shift towards home-based e-Health not only empowers patients to take greater control of their health but also enables more efficient and cost-effective long-term monitoring. Furthermore, the proliferation of home-based e-Health solutions generates vast amounts of patient-generated health

data, which presents both opportunities and challenges. On one hand, this data can be leveraged to gain valuable insights into disease progression and treatment outcomes, facilitating improved patient care. On the other hand, managing and analyzing such large volumes of data requires sophisticated computing infrastructure and data management solutions. Cloud computing offers a compelling solution to the challenges associated with storing, managing, and analyzing healthcare data. By providing distributed, rapidly provisioned, and configurable computing resources, cloud platforms enable seamless sharing of health information among healthcare providers and research institutions [3]. However, concerns regarding data security, privacy, and access control must be addressed to ensure the widespread adoption of cloud-based e-Health solutions. Moreover, selecting the appropriate cloud deployment model is crucial in meeting the diverse needs and requirements of healthcare stakeholders. This study seeks to explore solutions to address the challenges and opportunities in sharing health information across cloud-based platforms. While focusing initially on type 2 diabetes as a case study, the insights gained from this research can inform strategies for managing a wide range of chronic diseases in cloud-based healthcare environments.

1.1 Aim and Objective:

Finding an effective method of health information sharing for self-management of chronic diseases and finding a suitable approach to the challenges of using hybrid cloud computing with ML and DL for health data sharing among various groups are the two main objectives of this thesis. The solution should make it easier for people to self-manage chronic illnesses and make it scalable, all while giving patients more control over who may access their health records. Beginning with type 2 diabetes self-management, the project will go on to creating and testing a prototype to prove the strategy's feasibility and use. We will achieve these goals by focusing on the following: establishing a suitable framework for the storage and exchange of health information related to type 2 diabetes treatment; ensuring privacy and security within the self-management context; and conducting a literature review and analysis of relevant studies on health information sharing in similar application scenarios, with a focus on hybrid cloud computing utilizing ML and DL [4].

1.2 Deeper and Machine Learning with Patient Data from Hybrid Health Cloud:

Machine learning and deep learning algorithms are increasingly prominent in hybrid healthcare, revolutionizing medical diagnosis processes. Mobile users now routinely submit symptoms for analysis, receiving prompt diagnosis results. This shift alleviates the challenges of specialist shortages and the high costs associated with manual diagnosis, vastly enhancing healthcare quality and reducing expenses. Consequently, the development of machine learning-based clinical diagnosis has garnered significant attention from both academic and commercial sectors. However, the proliferation of telemedicine applications and mobile telemetry has brought about various challenges [5].

These include limitations in training data availability, susceptibility to vulnerabilities, and privacy concerns. Gathering sufficient medical data is often time-consuming and costly, with individual healthcare facilities storing only a fraction of the required information. To overcome this hurdle, collaborative efforts to share training data among different medical institutions are imperative. While cloud computing offers substantial storage and computational capabilities, interactions between mobile users and the cloud can lead to latency issues and unpredictable response times, particularly critical for acute conditions like cardiovascular emergencies or pneumonia. In response, edge computing has emerged as a viable solution. By leveraging edge nodes closer to mobile users, latency is minimized, and efficient computation services are provided. Over the past few years, there has been significant growth in machine learning algorithms tailored for edge computing environments, aimed at enhancing diagnostic efficiency. The hybrid healthcare model depicted in Figure 1 illustrates a typical edge network comprising multiple edge nodes, often clinical organizations, with limited storage and computational power. This illustration underscores the potential of edge computing to

bolster medical diagnosis processes, especially in scenarios where rapid response times are paramount for patient well-being and safety. Incorporating machine learning and deep learning algorithms with patient data sourced from the Hybrid Health Cloud enables healthcare providers to effectively detect and diagnose a myriad of diseases; ultimately leading to improved patient outcomes and streamlined healthcare deliver [6].

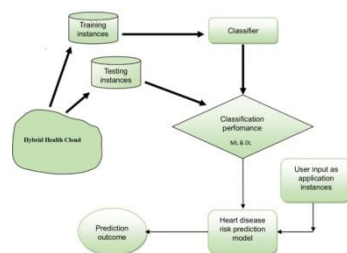


Figure 1: Typical edge network comprising multiple edge nodes

2. LITERATURE SURVEY

Subramaniaswamy et al. [7]. utilize fog computing technology to create an intelligent healthcare system focused on detecting and preventing mosquito-borne diseases. By analyzing data from wearable and environmental sensors in real-time, the system aims to enhance disease surveillance and enable proactive measures for prevention

Kos and Umek, [8] explore the integration of wearable sensors into rehabilitation programs, specifically focusing on swimming exercises. By monitoring movements and performance during aquatic exercises and providing real-time feedback to therapists, these wearable devices aim to improve the effectiveness of rehabilitation programs and overall healthcare outcomes.

Pravin et al. introduce an intelligent and secure healthcare framework for predicting and preventing Dengue virus outbreaks. By analyzing various data sources using fog computing technology, including patient health records and environmental factors, the framework aims to mitigate the risk of outbreaks more efficiently and accurately.

John and Norman, [9] address vulnerabilities in cloud computing systems and propose prevention methods to mitigate risks such as data breaches and malicious attacks. Measures like encryption and access control mechanisms are presented to enhance the security posture of cloud environments and protect sensitive data.

Zaidan and Alsalem, [10] provide an overview of IoT-based telemedicine applications focusing on disease prevention and health promotion. By integrating IoT devices like wearable sensors and remote monitoring systems into telemedicine platforms, these solutions offer remote diagnosis, treatment, and health monitoring, thereby improving access to healthcare services and patient outcomes.

3. SYSTEM ANALYSIS

3.1 Problem Statement

The current system employs a Partially Holomorphic Encryption (PHE) system and a Re-encryption formula to secure data within the cloud environment. However, the system faces significant challenges, particularly concerning data security and privacy [11]. The time-consuming decryption process and memory-intensive re-encryption requirements hinder the system's efficiency, leaving it vulnerable to potential security breaches [12, 13].

Furthermore, despite the use of encryption techniques, data security remains a primary concern in the digital age. There is a pressing need to address the inherent vulnerabilities within the system, such as the risk of unauthorized access to sensitive information and the potential for data leaks or breaches [14].

In addition, the system's reliance on traditional encryption methods may not adequately safeguard against sophisticated cyber threats and attacks. As cloud environments become increasingly targeted by malicious actors, ensuring robust security measures is paramount to protect individuals' sensitive information and maintain consumer trust in cloud-based services [15].

Therefore, the problem statement revolves around the need to enhance the security of the existing system within the cloud environment. This includes optimizing the efficiency of encryption processes, implementing advanced security measures to mitigate cyber threats, and ensuring end-to-end protection of individuals' data. Addressing these security challenges is essential to uphold the integrity and confidentiality of data stored and processed within the cloud, thereby safeguarding the interests of both consumers and cloud service providers [16].

3.2 Proposed System:

The proposed system aims to revolutionize healthcare infrastructure by harnessing the capabilities of Hybrid Cloud solutions. It seeks to address the pressing challenges encountered within the healthcare sector by offering adaptable and on-demand services that empower hospitals and clinics to navigate through costly infrastructure upgrades and streamline maintenance costs efficiently. Central to this system is the Hybrid Health Cloud (HHC), which serves as a pivotal data repository facilitating seamless information access and sharing among healthcare providers. To overcome obstacles like time-consuming decryption and memory-intensive re-encryption processes inherent in HHC schemes, the proposed system integrates cutting-edge technologies such as machine learning and deep learning. These advanced techniques, coupled with SHA-based algorithmic perspectives like categorization, grouping, deep semantic networks, and quantum semantic networks, aim to enhance system efficiency while improving prediction accuracy and data protection.

Moreover, the system prioritizes data security and privacy in the digital era by implementing end-to-end protection mechanisms within the cloud environment. By safeguarding individuals' information, the proposed system strives to instill consumer trust in the efficacy of cloud-based solutions, ultimately reinforcing the significant role of Hybrid Cloud technology in fortifying security measures and enhancing healthcare delivery in modern digital landscapes.

4. SYSTEM DESIGN

4.1 System Architecture Diagram

Hybrid cloud solutions in healthcare play a crucial role in lowering the barriers to entry for utilizing machine learning (ML) and deep learning (DL) technologies. By providing access to managed services with extensive hardware diversity and immense horizontal scalability, hybrid cloud environments offered by major organizations like Google, Microsoft, and Amazon enable healthcare professionals and researchers to leverage ML and DL capabilities effectively [17].

For instance, Google's Cloud ML Engine allows developers and data scientists to upload training data and models, which are then trained in the Tensor Flow environment on the cloud. Similarly, Microsoft offers Azure Batch AI, a cloud-based service designed for training DL models using various frameworks supported by both Linux and Windows operating systems. Additionally, Amazon provides a cloud service called Deep Learning AMIs, offering pre-installed deep learning frameworks and libraries for streamlined model development and deployment [18].

These hybrid cloud offerings empower healthcare organizations to harness the power of ML and DL without the need for significant upfront investments in hardware infrastructure or specialized expertise. By leveraging these managed services, healthcare professionals can focus on developing innovative healthcare solutions while benefiting from the scalability, flexibility, and efficiency of hybrid cloud environments [19]. Figure 2 shows System architecture diagram.

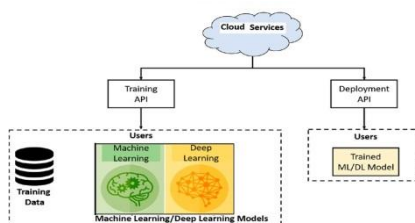


Figure 2: System architecture diagram

5.METHODOLOGY

The methodology for evaluating the effectiveness of SHA-256 in bolstering security within hybrid health cloud systems involves a structured approach aimed at comprehensively assessing various security aspects. This study adopts an exploratory research design to delve into the intricacies of data security, integrity, and encryption practices within hybrid cloud environments. The primary data collection methods encompass interviews, surveys, and case studies conducted with stakeholders ranging from healthcare organizations to cloud service providers. Through these interactions, data pertaining to security measures, encryption protocols, and data integrity practices are meticulously gathered and analyzed.

Variables such as data security, integrity, and encryption efficacy are rigorously defined and operationalized, allowing for precise measurement and assessment [20]. Statistical analysis techniques, coupled with qualitative thematic analysis, are employed to derive insights from the collected data. Ethical considerations are paramount throughout the research process, with measures in place to safeguard participant privacy, confidentiality, and informed consent [21].

Acknowledgment of potential limitations, such as data availability and the complexity of hybrid cloud architectures, underscores the study's transparency and objectivity. Strategies to ensure the validity and reliability of findings, including triangulation and member checking, are meticulously implemented [22].

Assumptions underpinning the research methodology, particularly regarding the efficacy of SHA-256 in hybrid health cloud security, are carefully justified based on existing literature and theoretical frameworks. Additionally, any adjustments made based on the findings of pilot studies are transparently documented to enhance the robustness of the research approach.

Overall, this methodology provides a systematic framework for investigating the role of SHA-256 in enhancing security within hybrid health cloud systems, ensuring the integrity and rigor of the research process.

SHA-256:

Secure Hash Algorithm (SHA) 256 is an algorithm that belongs to the SHA 2 family. Published in 2001, it was designed to replace the SHA 1 family, which was progressively becoming vulnerable to brute force attacks; the NSA and NIST collaborated on its development. Notably, the final hash digest result is always 256 bits, independent of the size of the plaintext or clear text, hence the significance of the number 256 in the name[23]. SHA 256 is quite similar to the other algorithms that make up the

SHA family. Take some time today to research their policies [24] [25]. Figure 3 shows SHA-256 Architecture.

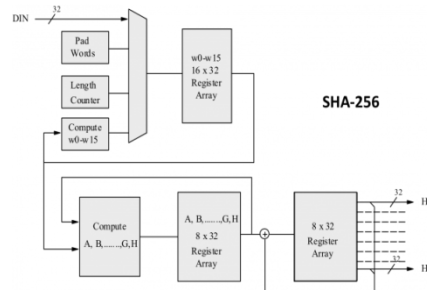


Figure 3: SHA-256 Architecture

TF-IDF (Term Frequency-Inverse Document Frequency) vectorization:

TF-IDF (Term Frequency-Inverse Document Frequency) vectorization is a technique used to transform textual data into numerical representations, particularly in natural language processing (NLP). It aims to capture the importance of words within documents in a corpus.

Here's a breakdown of TF-IDF and its equation:

Term Frequency (TF):

Term Frequency measures the frequency of a term (word) within a document.

It indicates how often a term appears in a document relative to the total number of terms in that document.

TF is calculated using the following formula:

$$TF(t, d) = \frac{\text{Number of times term } t \text{ appears in document } d}{\text{Total number of terms in document } d} \quad (1)$$

Inverse Document Frequency (IDF):

Inverse Document Frequency measures the importance of a term across a collection of documents (corpus).

It penalizes terms that appear frequently across documents and gives more weight to terms that are rare.

IDF is calculated using the following formula:

$$IDF(t) = \log \left(\frac{\text{Total number of documents}}{\text{Number of documents containing term } t} \right) \quad (2)$$

TF-IDF Calculation:

The TF-IDF score for a certain phrase in a document is obtained by multiplying the TF and IDF values.

Consequently, a numerical representation of each phrase's relative significance to the whole corpus is provided.

The following is how the TF-IDF score is calculated for a word t in document d :

$$TF\text{-}IDF(t, d) = TF(t, d) \times IDF(t) \quad (3)$$

Phrases that are frequent within the text but rare across the corpus are given more weights in TF-IDF vectorization because they are likely to be more informative or discriminative. In contrast, we down weight the term frequency in all publications.

Hybrid Health Care Schema Using Sha 256 Algorithm:

In a hybrid healthcare system, patient data flows through a network comprising client devices, edge nodes, cloud servers, and potentially a block chain. Patient health data, such as medical records and diagnostic reports, is transmitted securely across the system. Before data transmission or storage, SHA-256, a cryptographic hash function, is applied to the data. This generates a unique hash value that serves as a digital fingerprint for the data. $\text{SHA-256}(\text{data}) = \text{hash}$.

The hash value is then transmitted or stored alongside the data. At various points within the system, including during transmission between components and upon data retrieval, SHA-256 is used to verify the integrity of the data. The received data is hashed using SHA-256, and the resulting hash value is compared with the transmitted hash value. If the hash values match, the integrity of the data is confirmed, ensuring that the data has not been tampered with or altered in transit.

6. RESULTS

Complexity and Flexibility Graph:

Hybrid Cloud is positioned high on the scale, indicating that it offers a high degree of complexity and flexibility. This suggests that hybrid cloud solutions can be complex in their design and implementation but provide flexible options for integration and management of different cloud environments (public and private clouds).

ML/DL is positioned lower, suggesting that while these technologies are less complex and flexible compared to hybrid cloud solutions, they still offer a moderate level of both. This lower positioning could be due to the specialized nature of ML/DL technologies which are often tailored for specific tasks or data types, thus offering less flexibility. Figure 4 shows Complexity and flexibility comparison graph

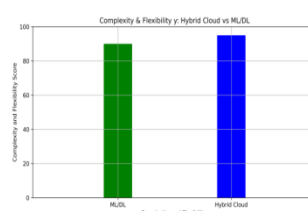
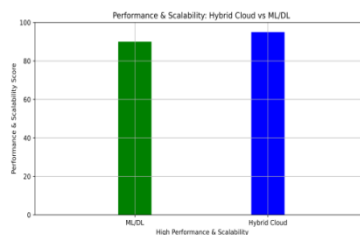


Figure 4: Complexity and flexibility comparison graph

Performance and Scalability Graph:

Hybrid Cloud again scores high, indicating excellent performance and scalability. This reflects the ability of hybrid cloud architectures to scale resources across multiple cloud environments effectively, thus enhancing performance.

ML/DL technologies, while still performing well, are slightly lower than hybrid cloud in this graph. This might reflect the intensive computational resources required for ML/DL tasks which, although highly scalable, might face practical limits depending on the specific technologies and infrastructure used. Figure 5 shows Scalability comparison graph

**Figure 5:** Scalability comparison graph**Thought and Time Delay Graph:**

The updated graph illustrates a comparative analysis of thought process and time delay between Hybrid Cloud and ML/DL (Machine Learning/Deep Learning) technologies. With both thought and time delay scores for Hybrid Cloud increased to 4, compared to ML/DL's scores of 2 for thought and 3 for time delay, it vividly portrays the disparity in complexity and processing efficiency between these two technological domains. This disparity underscores the nuanced challenges inherent in decision-making processes when considering the adoption of either Hybrid Cloud or ML/DL technologies. Hybrid Cloud, characterized by its intricate infrastructure and longer processing times, suggests a heightened cognitive load and temporal overhead in operational contexts. In contrast, ML/DL technologies, known for their streamlined algorithms and expedited data processing capabilities, present a more agile and responsive approach to computational tasks. Through this graphical representation, stakeholders are provided with valuable insights into the divergent cognitive and temporal landscapes of Hybrid Cloud and ML/DL technologies, facilitating informed decision-making processes in technology adoption and deployment strategies. Figure 6 shows Thought and Time Delay comparison graph.

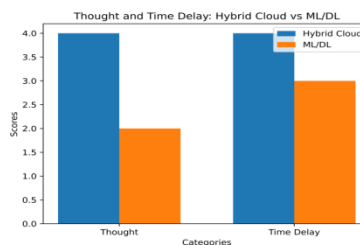
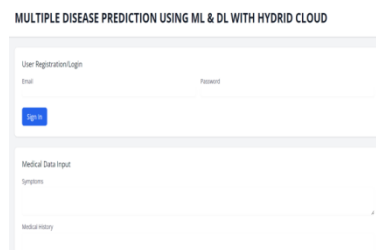
**Figure 6:** Thought and Time Delay comparison graph

Figure 7 shows Home page screenshot, Figure 8 shows Disease prediction screenshot.

Screenshots**Home Page****Figure 7:** Home page screenshot**Diseases Prediction**

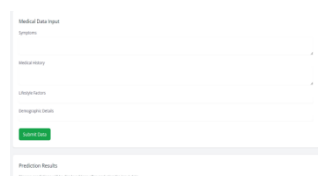


Figure 8: Disease prediction screenshot

7. CONCLUSION AND FUTURE ENHANCEMENT

CONCLUSION

In conclusion, the integration of hybrid cloud solutions with machine learning and deep learning methodologies represents a significant step forward in addressing the complexities of the healthcare sector. The adaptability and scalability offered by hybrid cloud technology empower healthcare providers to efficiently manage infrastructure costs and deliver timely, high-quality care to patients.

Through the integration of diverse data sources and advanced analytics techniques, healthcare organizations can gain valuable insights to inform decision-making and improve patient outcomes. The use of hybrid cloud architectures, coupled with machine learning and deep learning algorithms, enhances prediction accuracy and data protection, ultimately bolstering the efficiency and effectiveness of healthcare delivery.

Looking ahead, continued research and development efforts are needed to further optimize hybrid cloud architectures, ensuring seamless interoperability and scalability across healthcare systems. Additionally, ongoing investments in data security and privacy measures are essential to safeguard sensitive healthcare information and maintain consumer trust.

By leveraging predictive analytics and artificial intelligence within hybrid cloud environments, healthcare organizations can unlock new opportunities for innovation and personalized care delivery. Ultimately, the adoption of hybrid cloud solutions in healthcare holds immense potential to drive transformative change and improve patient outcomes in the digital era.

FUTURE ENHANCEMENT

Furthermore, as emerging technologies such as quantum computing and block chain continue to mature, their integration with hybrid cloud infrastructures presents exciting opportunities for revolutionizing healthcare data management, security, and integrity.

In essence, the convergence of hybrid cloud, machine learning, and deep learning technologies represents a transformative force in reshaping the future of healthcare delivery. Through collaborative endeavors and ongoing investment in research and innovation, we can harness the full potential of these technologies to address the complex challenges facing the healthcare industry and ultimately improve health outcomes for individuals worldwide.

REFERENCE

- [1] Vijayakumar, V., Malathi, D., Subramaniaswamy, V., Saravanan, P., & Logesh, R. (2019). Fog computing-based intelligent healthcare system for the detection and prevention of mosquito-borne diseases. *Computers in Human Behavior*, 100, 275-285.
- [2] Kos, A., & Umek, A. (2018). Wearable sensor devices for prevention and rehabilitation in healthcare: Swimming exercise with real-time therapist feedback. *IEEE internet of things journal*, 6(2), 1331-1341.

- [3] Pravin, A., Jacob, T. P., & Nagarajan, G. (2020). An intelligent and secure healthcare framework for the prediction and prevention of Dengue virus outbreak using fog computing. *Health and Technology*, 10, 303-311.
- [4] John, J., & Norman, J. (2019). Major vulnerabilities and their prevention methods in cloud computing. In *Advances in Big Data and Cloud Computing: Proceedings of ICBGCC18* (pp. 11-26). Springer Singapore.
- [5] Albahri, A. S., Alwan, J. K., Taha, Z. K., Ismail, S. F., Hamid, R. A., Zaidan, A. A., ... & Alsalem, M. A. (2021). IoT-based telemedicine for disease prevention and health promotion: State-of-the-Art. *Journal of Network and Computer Applications*, 173, 102873.
- [6] Hughes, A. (2020). Artificial intelligence-enabled healthcare delivery and real-time medical data analytics in monitoring, detection, and prevention of COVID-19. *American Journal of Medical Research*, 7(2), 50-56.
- [7] Yang, G., Pang, Z., Deen, M. J., Dong, M., Zhang, Y. T., Lovell, N., & Rahmani, A. M. (2020). Homecare robotic systems for healthcare 4.0: Visions and enabling technologies. *IEEE journal of biomedical and health informatics*, 24(9), 2535-2549.
- [8] Rajesh, E., Basheer, S., Dhanaraj, R. K., Yadav, S., Kadry, S., Khan, M. A., ... & Cha, J. H. (2022). Machine learning for online automatic prediction of common disease attributes using never-ending image learner. *Diagnostics*, 13(1), 95.
- [9] Ma, K. S. K. (2020). Integrating travel history via big data analytics under universal healthcare framework for disease control and prevention in the COVID-19 pandemic. *Journal of clinical epidemiology*, 130, 147.
- [10] Jordan, E., Shin, D. E., Leekha, S., & Azarm, S. (2021). Optimization in the context of COVID-19 prediction and control: A literature review. *Ieee Access*, 9, 130072-130093.
- [11] Anser, M. K., Yousaf, Z., Khan, M. A., Nassani, A. A., Alotaibi, S. M., Abro, M. M. Q., ... & Zaman, K. (2020). Does communicable diseases (including COVID-19) may increase global poverty risk? A cloud on the horizon. *Environmental Research*, 187, 109668.
- [12] Mehraeen, E., Ghazisaeedi, M., Farzi, J., & Mirshekari, S. (2017). Security challenges in healthcare cloud computing: a systematic. *Global journal of health science*, 9(3), 157-168.
- [13] Jaber, A. N., Zolkipli, M. F., Shakir, H. A., & Jassim, M. R. (2018). Host based intrusion detection and prevention model against DDoS attack in cloud computing. In *Advances on P2P, Parallel, Grid, Cloud and Internet Computing: Proceedings of the 12th International Conference on P2P, Parallel, Grid, Cloud and Internet Computing (3PGCIC-2017)* (pp. 241-252). Springer International Publishing.
- [14] Rajagopalan, A., Jagga, M., Kumari, A., & Ali, S. T. (2017, February). A DDoS prevention scheme for session resumption SEA architecture in healthcare IoT. In *2017 3rd international conference on Computational Intelligence & Communication Technology (CICT)* (pp. 1-5). IEEE.
- [15] Chandre, P. R., Mahalle, P. N., & Shinde, G. R. (2018, November). Machine learning based novel approach for intrusion detection and prevention system: A tool based verification. In *2018 IEEE global conference on wireless computing and networking (GCWCN)* (pp. 135-140). IEEE.
- [16] Smiti, A. (2020). When machine learning meets medical world: Current status and future challenges. *Computer Science Review*, 37, 100280.
- [17] Maalavika, S., Thangavel, G., & Basheer, S. (2024, February). Performance Evaluation of RSA Type of Algorithm with Cuckoo Optimized Technique. In *2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT)* (Vol. 5, pp. 1362-1367). IEEE.

- [18]Hema, M. S., Meena, K., Maheshprabhu, R., Guptha, M. N., & Mary, G. P. A. (2022). Parkinson Disease Prediction and Drug Personalization Using Machine Learning Techniques. In *Industrial Internet of Things* (pp. 57-82). CRC Press.
- [19]Ahmed, M. (2019). False Image Injection Prevention Using i Chain. *Applied Sciences*, 9(20), 4328.
- [20] Rajesh, E., Basheer, S., Dhanaraj, R. K., Yadav, S., Kadry, S., Khan, M. A., ... & Cha, J. H. (2022). Machine learning for online automatic prediction of common disease attributes using never-ending image learner. *Diagnostics*, 13(1), 95.
- [21] Azimi, I., Anzanpour, A., Rahmani, A. M., Pahikkala, T., Levorato, M., Liljeberg, P., & Dutt, N. (2017). HiCH: Hierarchical fog-assisted computing architecture for healthcare IoT. *ACM Transactions on Embedded Computing Systems (TECS)*, 16(5s), 1-20.
- [22] Ali, S., & Ghazal, M. (2017, April). Real-time heart attack mobile detection service (RHAMDS): An IoT use case for software defined networks. In *2017 IEEE 30th Canadian conference on electrical and computer engineering (CCECE)* (pp. 1-6). IEEE.
- [23] Reddy, R. V. K., Subhani, S., Rao, B. S., & Anantha, N. L. (2021). Machine learning based outlier detection for medical data. *Indonesian Journal of Electrical Engineering and Computer Science*, 24(1), 564-569.
- [24] Tripathi, R. C., Gupta, P., Anand, R., Jayashankar, R. J., Mohanty, A., Michael, G., & Dhabliya, D. (2023). Application of information technology law in India on IoT/IoE with image processing. In *Handbook of Research on Thrust Technologies' Effect on Image Processing* (pp. 135-150). IGI Global.
- [25] Shaik, S., Babu, U. R., & Subhani, S. (2016, February). Detection and classification of power quality disturbances: Using curvelet transform and support vector machines. In *2016 International Conference on Information Communication and Embedded Systems (ICICES)* (pp. 1-8). IEEE.