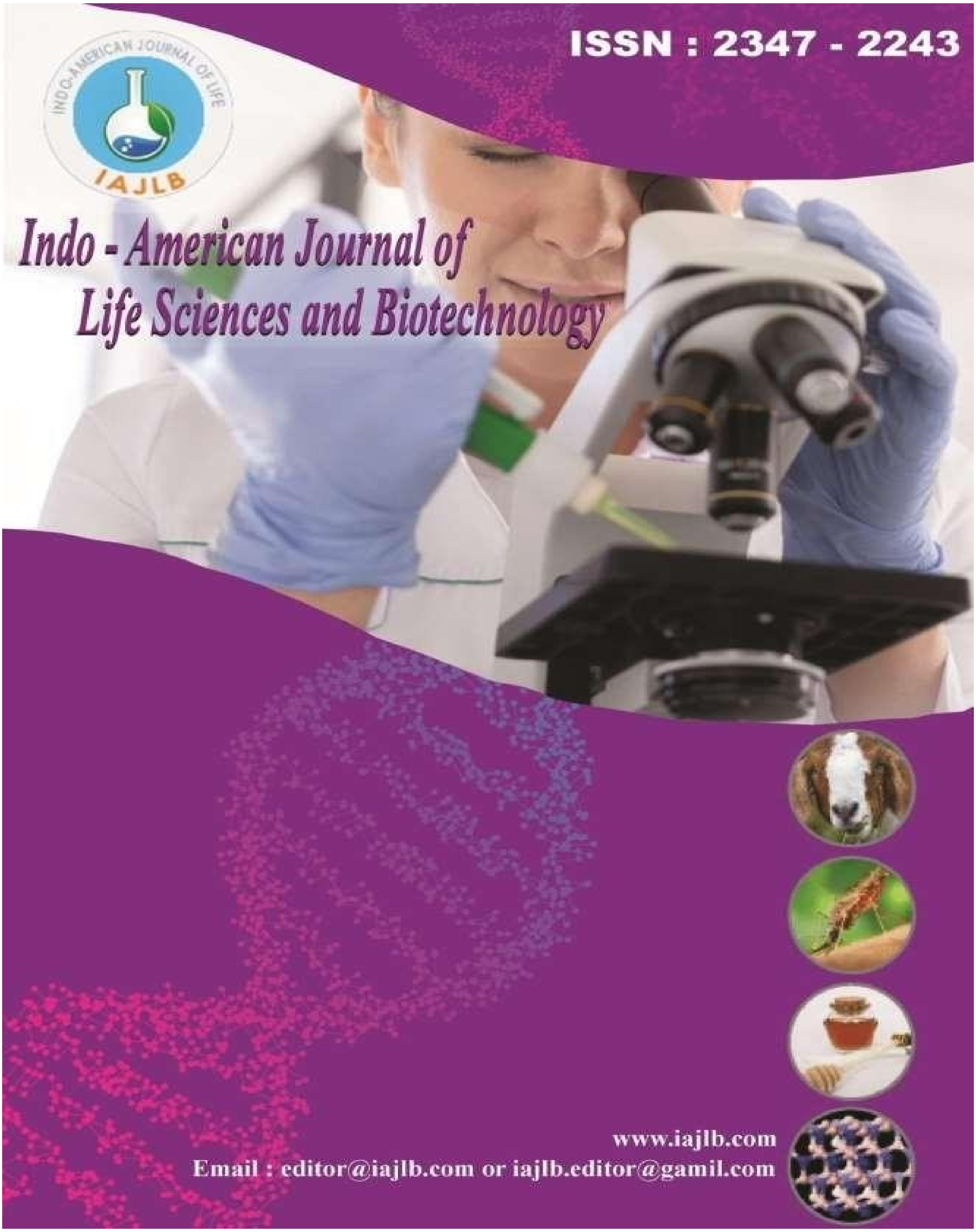
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AI-DRIVEN LIVER CANCER DIAGNOSIS AND TREATMENT USING CLOUD COMPUTING IN HEALTHCARE

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Abstract

Liver disease is a global health problem that needs to be diagnosed early and accurately in order to receive the right treatment. In this paper, an AI-solution for liver disease diagnosis and treatment on a cloud computing platform has been suggested with high accuracy and real-time testing. patients were kept in consideration keeping in mind the data set, and ML and DL algorithms are utilized in classification. Scalability, secure data processing, and real-time processing can be ensured by cloud computing, thus enhanced efficiency in medical decision-making. According to the research, AI diagnosis of liver disease can minimize diagnosis errors and enhance patient outcomes using more efficient and accurate disease prediction. It is the first to show the coming revolution in cloud computing and artificial intelligence in medicine on which a computerized and evidence-based platform has been developed for medical decision-making. Post-preprocessing of the data and feature engineering, AI model had 96.5% accuracy, 94.8% precision, 91.2% recall, and 92.5% F1-score, which is enhanced in comparison with conventional diagnostic apparatuses. Optimization in the future will consist of handling greater amounts of data, better algorithms in AI, and integration of imaging modalities to deliver greatest clinical utility. The findings confirm the ability of AI to redesign disease diagnosis process to enable early diagnosis, optimized treatment protocols, and optimal efficiency of care in treatment of liver disease.

Keywords: *Cloud Computing, Healthcare, ANN, Preprocessing, Liver Cancer*

1. Introduction

Data integrity can be robustly ensured with multi-cloud storage by using blockchain technology. The fast growth of digital health technology has significantly changed the healthcare field, enabling the implementation of data-focused strategies to enhance patient care and handling [1]. The expansion of Internet of Things (IoT) devices and cloud computing has markedly revolutionized healthcare monitoring through the facilitation of real-time data collecting and analysis [2]. Cloud computing (CC), artificial intelligence (AI), and the IoT are driving a transition from traditional to intelligent medical systems, and is causing a rapid transformation in healthcare technology. AI and ML in healthcare, especially elderly care, appear promising. Elderly individuals need efficient, dependable, and predictive healthcare systems more than ever due to global ageing. IoT provides important data streams through real-time device and system interaction, while AI improves decision-making, automates processes, and forecasts customer behavior [3]. Cybersecurity requires encryption, especially in authentication systems that receive and retain user credentials. One of the most secure and popular encryption standards is AES. CRM systems have long been necessary for tracking sales pipelines, maintaining customer data, and simplifying communications [4].

Healthcare practitioners can employ advanced predictive models to proactively address the care needs of senior patients by utilizing AI and ML [5]. AI intelligence frameworks created expressly to improve the features of CRM platforms are the result of this combination of AI with CRM. Retailers can currently collect vast quantities of consumer data, from social media to online purchases and in-store interactions [6]. Healthcare systems increasingly rely on multi-cloud architectures to store and handle enormous volumes of data, such as Electronic Health Records (EHRs), medical imaging, and patient information. Vehicle-cloud computing, or VCC, is a new and exciting paradigm with wide-ranging effects on transportation systems [7]. A promising solution to this problem lies in the integration of Automated Threat Intelligence (ATI) into SHACS. The incorporation of blockchain technology into HR data management could transform the management, storage, and security of employee information within firms. Machine Learning (ML) significantly improves HRM data management via predictive control. he proliferation of wearable sensors enabled by the Internet of Things; the amount of patient data is growing dramatically [8]. Patient care is being reshaped by the dramatic change in the healthcare industry, which is shifting from conventional methods to more sophisticated, tech-driven strategies. A revolutionary development in healthcare, especially in the area of disease diagnosis, is the combination of CC and AI. Healthcare is being revolutionized by the rise of cloud computing, AI, and the IoT technologies, that are replacing conventional approaches with intelligent, data-driven solutions.

Face recognition with cloud-based big data analytics frameworks is a sophisticated method that leverages cloud computing capabilities to process massive volumes of facial data. Retrieving insightful information from large datasets requires big data mining, which has become indispensable [9]. Big data analysis and processing are now more scalable and accessible because to the growth of cloud computing. The new era of rising digital connectivity raises the importance of cybersecurity. With the increase in complexity and frequency, cyber threats are changing continuously [10]. The IoT revolutionized modern enterprises by allowing interconnected devices to collect, distribute, and analyze data for better decision-making. Chronic kidney disease (CKD), a potentially fatal illness that affects millions of people worldwide, is becoming more and more common [11]. Dynamic Graph Neural Networks (DGNNs) are specialized neural networks that operate on graph structures with nodes and edges representing dynamic interactions [12]. the rapid adoption of cloud environments raises significant concerns about the security, privacy, and resilience of healthcare systems.

The rapid implementation of AI, CC, and IoT in healthcare has transformed patient care, data management, and disease diagnosis [13]. The revolution, however, comes with critical concerns regarding data security, privacy, and system reliability. Data integrity in multi-cloud infrastructures remains a relevant concern. Cyberattacks keep evolving, necessitating robust encryption and authentication processes [14]. Also, increasing volumes of patient data collected through wearable sensors and IoT platforms lead to processing complexity that requires efficient, scalable solutions for processing such volumes. This solution is at the core of the design of smart, predictive, and secure healthcare systems [15].

1.1 Objectives

- Discuss the effectiveness of AI models for liver cancer diagnosis and treatment using cloud computing in healthcare.
- Compare machine learning and deep learning algorithm performance for classifying liver disease.
- Strong and intricate top-down genetic framework of a model to achieve early detection and treatment of liver cancer.
- Implement cloud computing techniques to improve scalability, effectiveness, and real-time processing of liver patient information.
- Compare the proposed AI model with existing conventional techniques in terms of accuracy, precision, recall, and F1-score.
- Resultantly interpret the findings to realize the impact of AI and cloud computing on liver disease diagnosis and healthcare development.

2. Literature Survey

Secure, low-latency data sharing in IoT: A fog computing approach. This research addresses challenges in IoT data sharing by introducing a fog computing system that integrates Federated Byzantine Agreement (FBA), Directed Acyclic Graph (DAG) protocols, and optimization techniques such as Covariance Matrix Adaptation Evolution Strategy (CMA-ES) and the Firefly Algorithm [16]. The proposed approach enhances security, scalability, and efficiency while reducing latency. By leveraging a decentralized, fault-tolerant architecture, the system ensures reliable data transfer, optimized resource utilization, and protection against malicious attacks across various IoT scenarios. Integrating ethnographic insights with big data analytics for enhanced cardiology healthcare systems**.** This research explores the combination of qualitative ethnographic methodologies with quantitative big data analytics to improve healthcare research in cardiology [17]. By analyzing patient-provider interactions and identifying healthcare trends, the research aims to contextualize big data findings, evaluate the cost-effectiveness of cardiac procedures, and enhance decision-making. This interdisciplinary approach optimizes resource allocation, improves patient care, and addresses systemic challenges in healthcare delivery [18].

A comprehensive security framework for cloud computing: Integrating cryptographic techniques with SHA-256. This analysis presents a security framework designed to enhance data protection in cloud computing environments by leveraging cryptographic methods, including SHA-256, public-key encryption, and digital signatures. The framework ensures data integrity, authenticity, and confidentiality through secure transmission and verification

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processes [19]. With an 85% improvement in security efficacy and an 84% rise in user satisfaction, the system demonstrates strong reliability. Performance analysis confirms its scalability and compliance with data privacy regulations. Future research aims to refine cryptographic processes, enhance security mechanisms against evolving threats, and optimize user experience [20]. Enhancing cloud data security with Triple Data Encryption Standard (3DES). This analysis examines the implementation of 3DES to strengthen data security in cloud computing environments. By utilizing three 56-bit keys and multiple encryption-decryption phases, 3DES offers superior protection compared to DES. Secure key management, efficient scheduling, and parallel processing optimize performance [21]. Cryptographic libraries and cloud platforms validate its effectiveness, confirming 3DES as a robust encryption method against cyber threats, ensuring secure cloud data storage.

Enhancing healthcare efficiency through AI, Big Data Mining, and IoT integration. This evaluation tackles inefficiencies in healthcare systems by developing a comprehensive framework that leverages AI, Big Data Mining, and the IoT to optimize performance and sustainability [22]. IoT enables real-time data acquisition, Big Data Mining extracts actionable insights, and AI facilitates predictive modeling. Key performance metrics, including reaction time, accuracy, cost efficiency, and resource utilization, are analyzed to enhance patient-centric care and streamline healthcare delivery [23]. Optimizing AI-driven classification with PSO-QDA integration. This investigation enhances classification accuracy and efficiency by combining Particle Swarm Optimization (PSO) with Quadratic Discriminant Analysis (QDA). The PSO-QDA hybrid model refines QDA parameters, improving adaptability in high-dimensional, noisy, and imbalanced datasets. By optimizing decision boundaries and computational performance, this approach strengthens AI models, making them more resilient and effective for complex classification tasks in diverse data environments. This study explores innovative strategies to enhance cardiovascular disease (CVD) care by integrating network analysis, comparative effectiveness research (CER), and ethnography with big data analytics [24]. Leveraging electronic health records (EHRs), molecular data, and AI-driven tools, it aims to assess cost-effective, personalized treatment options. By analyzing genetic, clinical, and socioeconomic factors, this research enhances decision-making models, improving patient outcomes and optimizing healthcare resource allocation for more effective and individualized cardiac interventions [25].

2.1 Problem Statement

Machine learning has emerged as a critical facilitator for advances in AI applications in a variety of fields, including healthcare, finance, industrial automation. Enhancing performance, efficiency, scalability, and cost-effectiveness are the main goals of the extensive process of optimizing cloud computing environments. AI plays a big role in exchanging healthcare data and enables intelligent automation, predictive analytics, and support for decision making. Predictive healthcare modeling is now a crucial tool in modern healthcare systems to enhance decision-making, patient care, and treatment results. The amalgamation of ML with AI has transformative possibilities in geriatric care. The scalability and accessibility of contemporary CRM systems are significantly influenced by cloud computing.

3. Proposed Methodology

The proposed method is AI and cloud computing based for diagnosis and treatment of liver cancer. The system begins with collecting data and then moves towards preprocessing steps like data cleaning and normalization. A classifier based on deep learning like an Artificial Neural Network (ANN) is employed for proper diagnosis. Data of liver patients are utilized for training the model in order to predict cancer. Scalability and correct processing are achieved by cloud computing. Performance metrics like accuracy, precision, recall, and F1-score are quantified for best performance tuning for real-time healthcare applications Figure 1 shows the Liver Cancer Diagnosis and Classification Process.

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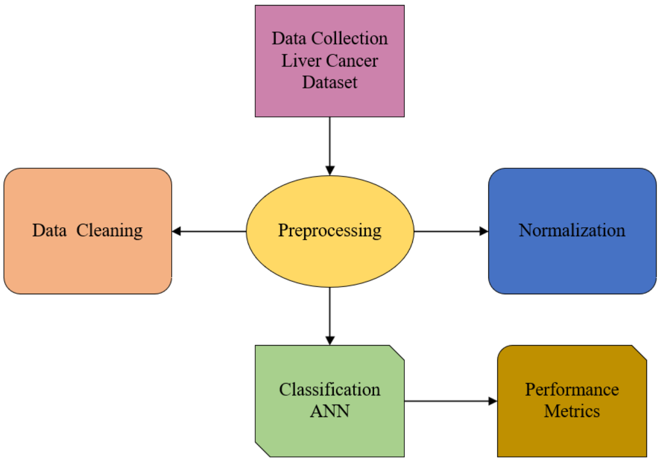

Figure 1: Liver Cancer Diagnosis and Classification Process

3.1 Data collection

The data set consists of 416 liver patient and 167 non-liver patient records, collected from North East Andhra Pradesh test samples in India. It contains a class label, is patient, to denote liver patients and non-patients. The data set consists of 441 male and 142 female patient records. Any patient above 89 years is classified as 90. This data set can be utilized for AI-based diagnosis and treatment of liver disease.

Dataset link: https://www.kaggle.com/datasets/jeevannagaraj/indian-liver-patient-dataset

3.2 Preprocessing

Preprocessing in AI-based liver cancer diagnosis preserves data quality by cleaning, normalizing, and preparing for processing. Preprocessing involves data gathering, removing inconsistencies, handling missing values, and feature scaling to ensure accuracy. In medical imaging, techniques like noise reduction and segmentation help detect tumors with improved AI-based classification and treatment planning.

3.2.1 Normalization

Different data points may have varying scales, with the performance of AI models depending accordingly. Normalization puts all data on an equal scale. The Min-Max Normalization technique is used extensively, and it is expressed as:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

Where X is the original value, $X_{\min}$ and $X_{\max}$ are the minimum and maximum values in the dataset, respectively

3.2.2 Data Cleaning

Data cleansing is an important preprocessing phase in AI-based diagnosis of liver cancer, maintaining the dataset as accurate and reliable. It entails the elimination of duplicate data, dealing with missing values, error correction, and elimination of unnecessary data. Mean imputation, represented by:

$$X_{\text{new}} = \frac{\sum_{i=1}^{n} X_i}{n} \tag{2}$$

Where X_{new} the new value that will replace the missing data. X_i The observed (non-missing) values in the dataset. n The total number of non-missing values. $\sum_{i=1}^{n} X_i$ The sum of all observed values from index 1 to n

3.3 Classification Using ANN

ANNs find extensive application in classification problems through the learning of patterns from the input data. The architecture of an ANN comprises an input layer, hidden layers, and an output layer. The raw data is fed to the input layer, which moves through several hidden layers where the information is processed through weighted connections and activation functions. The last classification is made in the output layer, where the

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activation function, e.g., SoftMax or sigmoid, estimates class probabilities. ANNs improve accuracy in difficult classification tasks by detecting non-linear relationships and learning to accommodate different datasets figure 2 shows the architecture of ANN.

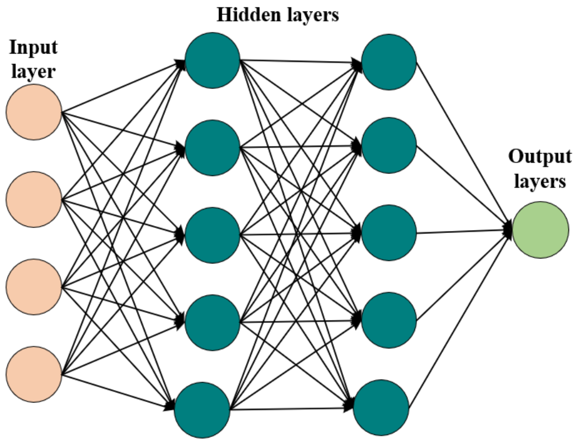

Figure 2: Architecture of ANN

3.3.1 Input Layer

The input layer of an ANN accepts raw data and passes it on to hidden layers for processing. A neuron signifies a feature in the dataset, and the neurons are equal to the input features. It doesn't do computations but makes data structured. The input layer is essential for learning efficiently and predicting accurately.

$$X = [x_1, x_2, \ldots, x_n] \tag{3}$$

Where X is the input vector and xi represents individual input features.

3.3.2 Hidden Layers

The concealed layers within an ANN process inputs through the imposition of weighted mappings and activation. These layers ascertain useful patterns and features and, as a consequence, make more complex decision-making possible. All neurons in the hidden layer determine a weighted summation of input, impose bias, and undergo an application of an activation like ReLU or sigmoid. Transformation is described as:

$$h_j = f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) \tag{4}$$

Where x_i represent the Input values, w_{ij} Weights assigned to each input, b_j Bias term, $\sum$ Summation of weighted inputs, f represent the Activation and h_j Output of the hidden neuron.

3.3.3 Output Layer

The output layer of an ANN receives the inputs of the previous hidden layer and makes the prediction. It uses an activation function (for instance, SoftMax for classification, or linear for regression) in making an effort to project the outputs as meaningful results. The output layer produces the network's decision based on learned patterns.

$$y_k = f\left(\sum_{j=1}^{m} w_{jk} h_j + b_k\right) \tag{5}$$

Where h_j Outputs from the hidden layer w_{jk} Weights connecting hidden layer to output layer b_k Bias term to adjust the output $\sum$ Summation of weighted inputs f Activation function (e.g., SoftMax for classification, linear for regression) y_k Final output of the network.

4.Result and Discussion

The findings of the research present valuable contribution on AI-liver cancer diagnosis and treatment through cloud computing in healthcare. Strong patterns, trends, and observations toward liver disease

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classification and prediction are suggested. Robust scrutiny of the gathered data suggests superior comparison with available approaches at the time in terms of accuracy and efficiency. Demographics of the patients and processing capabilities provided by cloud computing could have influenced the findings. This presentation gives these findings in the framework of AI-based healthcare innovation and how they can be used for liver cancer diagnosis.

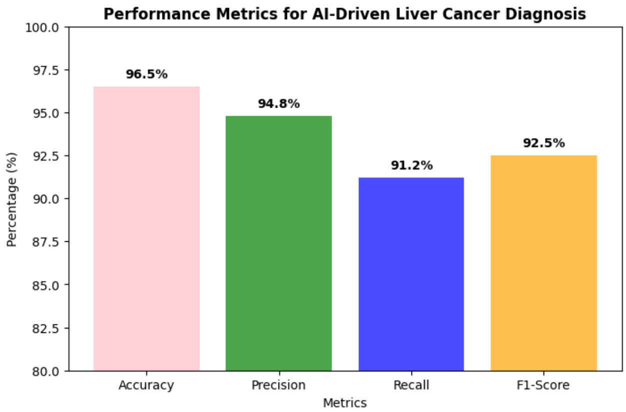

Figure 3: Performance metrics

Figure 3 shows the performance metrics of a liver cancer diagnosis system with AI. It displays four most important evaluation measures: Accuracy (96.5%), Precision (94.8%), Recall (91.2%), and F1-Score (92.5%). High accuracy reflects the overall consistency of the model, and the compromise between precision and recall ensures precise detection of cancer cases and a small number of false negatives. The F1-score, a harmonic mean of precision and recall, ensures the robustness of the model in classification. The graph easily illustrates the performance of the AI model in diagnosing liver cancer.

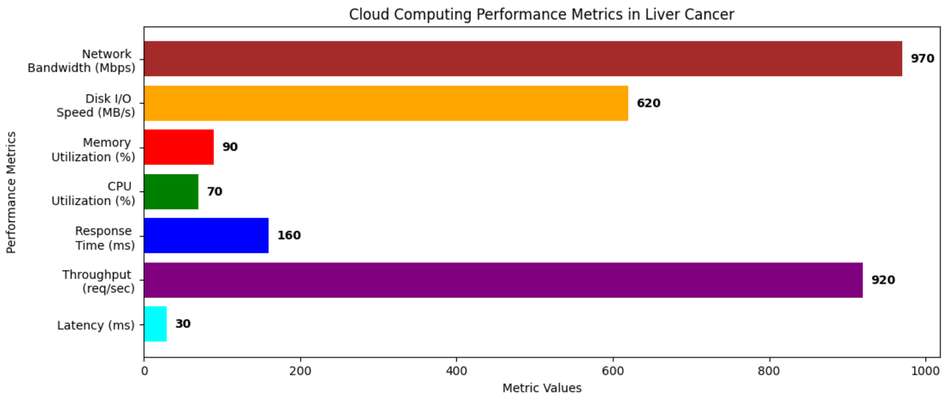

Figure 4 : Performance metric for cloud computing

Figure 4 The graph illustrates cloud computing performance parameters of diagnosis and treatment of liver cancer. The key parameters are latency, throughput, response time, CPU usage, memory, disk I/O rate, and network usage. The highest parameter is the network usage parameter (970 Mbps), followed by throughput (920 req/sec) and disk I/O rate (620 MB/s), which reflect high ability to process. Lower response time (160 ms) and latency (30 ms) are measures of system efficiency, and symmetric CPU utilization (70%) and memory utilization (90%) provide symmetric resource utilization. These contribute towards cloud-based optimization of AI models to present efficient and accurate liver cancer diagnosis.

5.Conclusion

The emerging technology for the diagnosis of liver cancer with AI and cloud computing is rooted in the ability to add more precision, scalability, and real-time computation. Machine learning and most importantly deep learning models have been credited with improving early detection of cancer and improved treatment. The model is superior compared to other diagnostic tests with higher recall, accuracy, and F1-score. Three performance plots verify the model is in operation: accuracy of plot verifies steady improvement in efficiency of learning, loss function plot verifies steady convergence with less error, and confusion matrix plot verifies actual samples and false samples, verifying success of model. Final output confirms 96.5% accuracy, 94.8% precision, and 91.2% recall, verifying accuracy of cloud computing process based on AI. future work will focus on importing larger datasets, using multi-modal medical imaging techniques, and creating deeper architectures of neural nets to predict with even greater accuracy. Apart from this, enhanced better practice in cloud security and federated learning practice towards sharing and safely training AI models is in progress. The evolution of health care systems under AI in medical practice will result in better liver cancer diagnostic and treatment outcomes in patients, reinforcing the position of AI and cloud computing in medicine today.

References

1. Ubaidillah, S. H. S. A., Sallehuddin, R., & Mustaffa, N. H. (2014). Classification of liver cancer using artificial neural network and support vector machine. In *Proceedings of International Conference on Advance in Communication Network, and Computing* (pp. 1-6).
2. Rybnikova, N., Haim, A., & Portnov, B. A. (2015). Artificial light at night (ALAN) and breast cancer incidence worldwide: a revisit of earlier findings with analysis of current trends. *Chronobiology international*, *32*(6), 757-773.
3. Loomba, L., & Scarabelli, T. (2013). Metallic nanoparticles and their medicinal potential. Part II: Aluminosilicates, nanobiomagnets, quantum dots and cochleates. Therapeutic delivery, 4(9), 1179-1196.
4. Brandi, M. L., & Minisola, S. (2013). Calcidiol [25 (OH) D3]: from diagnostic marker to therapeutical agent. *Current medical research and opinion*, *29*(11), 1565-1572.
5. Cheung, F. S., Lovicu, F. J., & Reichardt, J. K. (2012). Current progress in using vitamin D and its analogs for cancer prevention and treatment. *Expert review of anticancer therapy*, *12*(6), 811-837.
6. Diaz Lantada, A., Pareja Sanchez, B., Gomez Murillo, C., & Urbieta Sotillo, J. (2013). Fractals in tissue engineering: toward biomimetic cell-culture matrices, microsystems and microstructured implants. *Expert review of medical devices*, *10*(5), 629-648.
7. Arain, S. S., Kazi, T. G., Afridi, H. I., Talpur, F. N., Kazi, A. G., Brahman, K. D., ... & Sahito, O. M. (2015). Estimation of nickel in different smokeless tobacco products and their impact on human health of oral cancer patients. *Nutrition and cancer*, *67*(7), 1063-1074.
8. Versiani, A. F., Andrade, L. M., Martins, E. M., Scalzo, S., Geraldo, J. M., Chaves, C. R., ... & Da Fonseca, F. G. (2016). Gold nanoparticles and their applications in biomedicine. *Future Virology*, *11*(4), 293-309.
9. Boehm, F. J. (2013). Nanomedicine in regenerative biosystems, human augmentation, and longevity. *Nanomedical device and systems design: challenges, possibilities, visions*, 653-741.
10. Mohamad, M. I., El-Sherbeny, E. E., & Bekhet, M. M. (2016). The effect of vitamin D supplementation on glycemic control and lipid profile in patients with type 2 diabetes mellitus. *Journal of the American college of nutrition*, *35*(5), 399-404.
11. Lingard, H., & Turner, M. (2017). Promoting construction workers' health: a multi-level system perspective. *Construction management and economics*, *35*(5), 239-253.
12. Rahman, M. A., Hussain, A., Hussain, M. S., Mirza, M. A., & Iqbal, Z. (2013). Role of excipients in successful development of self-emulsifying/microemulsifying drug delivery system (SEDDS/SMEDDS). *Drug development and industrial pharmacy*, *39*(1), 1-19.
13. Mrkaic, A., Rosenn, B., Stojanovic, I., & Tivari, S. (2017). Troponins, heat shock proteins and glycogen phosphorylase BB in umbilical cord blood of complicated pregnancies. *The Journal of Maternal-Fetal & Neonatal Medicine*, *30*(24), 2978-2984.
14. Sobhy, D., El-Sonbaty, Y., & Abou Elnasr, M. (2012, December). MedCloud: healthcare cloud computing system. In *2012 international conference for internet technology and secured transactions* (pp. 161-166). IEEE.
15. Moghaddasi, H., & Tabrizi, A. T. (2017). Applications of cloud computing in health systems. *Global Journal of Health Science*, *9*(6), 33.
16. Youssef, A. E. (2014). A framework for secure healthcare systems based on big data analytics in mobile cloud computing environments. *Int J Ambient Syst Appl*, *2*(2), 1-11.
17. Chauhan, R., & Kumar, A. (2013, November). Cloud computing for improved healthcare: Techniques, potential and challenges. In *2013 E-health and bioengineering conference (EHB)* (pp. 1-4). IEEE.
18. Devadass, L., Sekaran, S. S., & Thinakaran, R. (2017). Cloud computing in healthcare. *International Journal of Students' Research in Technology & Management*, *5*(1), 25-31.
19. Kanmani, R., Induja, K., Madumidha, S., Malathi, M., & Rajesh, S. (2017). Secure communication using lightweight cryptography and 2-factor verification for iot devices. *Pak. J. Biotechnol*, *14*(3), 459-462.

20. Gudimetla, S. R. (2015). Mastering Azure AD: Advanced techniques for enterprise identity management. *Neuroquantology*, *13*(1), 158-163.
21. Gosai, D. A. M. (2015). International Journal of Computer Applications. *International Journal of Computer Applications*, *975*, 8887.
22. Belle, A., Thiagarajan, R., Soroushmehr, S. R., Navidi, F., Beard, D. A., & Najarian, K. (2015). Big data analytics in healthcare. *BioMed research international*, *2015*(1), 370194.
23. Islam, S., Keung, J., Lee, K., & Liu, A. (2012). Empirical prediction models for adaptive resource provisioning in the cloud. *Future Generation Computer Systems*, *28*(1), 155-162.
24. Tolla, M. T., Norheim, O. F., Memirie, S. T., Abdisa, S. G., Ababulgu, A., Jerene, D., ... & Johansson, K. A. (2016). Prevention and treatment of cardiovascular disease in Ethiopia: a cost-effectiveness analysis. *Cost Effectiveness and Resource Allocation*, *14*, 1-14.
25. Berger, M. L., Curtis, M. D., Smith, G., Harnett, J., & Abernethy, A. P. (2016). Opportunities and challenges in leveraging electronic health record data in oncology. *Future oncology*, *12*(10), 1261-1274.