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AI-Driven Cloud Solutions for Scalable and Secure Diabetes Prediction in Healthcare Systems

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ABSTRACT

Diabetes is a fast-growing global health problem affecting thousands across the world. Early diagnosis and effective management can help avoid the full-blown consequences of complications such as heart disease and kidney failure. Conventional methods of diagnosis are often inaccurate, slow, and do not scale for larger datasets. This work proposes an AI-cloud-based diabetes-predicting model that puts a premium on data security by using Blockchain along with AI/ML for decision-making. The model aims to be secure, scalable, and efficient for predicting whether a patient is diabetic in terms of clinical parameters like glucose levels, BMI, age, and insulin. While the proposed system uses Blockchain technology for decentralized storage, feature extraction is conducted using Random Forest, and training is done using the Multilayer Perceptron (MLP). The proposed prediction model works on cloud infrastructure for training and deployment--thereby ensuring scalability and real-time access. The evaluation results indicated that the proposed solution surpassed the traditional methods in accuracy (98.25%), precision (98.46%), recall (98.46%), and AUC-ROC (0.981). The proposed solution thus provides enhanced data security, scalability, and predictive accuracy and is an efficient and secure instrument for diabetes prediction for practitioners to intervene timely for better patient outcomes.

Keywords: Diabetes Prediction, Cloud Computing, Blockchain Technology, Machine Learning, Data Security, Scalable Systems

1. INTRODUCTION

Diabetes, an ever-increasing global health concern, is getting prevalent due to a sedentary lifestyle, unhealthy eating habits, and genetic inheritance [1]. According to the World Health Organization (WHO), more than 460 million adults were living with diabetes; it is presumed that the number will continuously increase in the future [2]. The most important phase in the entire management cycle of diabetes is the early detection of diabetes and its proper management because it can help reduce complications like cardiovascular diseases, kidney failure, and blindness [3]. Older methods of diabetes detection are also associated with manual assessment procedures that take a long time and are prone to errors and are not scalable [4]. In recent years, they have greatly enhanced the use of artificial intelligence (AI)-based tools and machine learning models in healthcare to supplement diagnostics and improve healthcare pathways [5]. Cloud computing is an emerging technology that, through keeping massive volumes of bulk data and scalable computing power, has proven to be an important part in making the whole AI-enabled healthcare possible [6]. The combination of AI and cloud computing promises an excellent combination for diabetes prediction systems constructed as scalable, secure, and efficient [7]. Such systems can operate in real healthcare environments [8].

Diabetes mellitus is a chronic metabolic disorder characterized by elevated blood glucose levels, affecting millions of people worldwide [9]. With its growing prevalence, diabetes has become a significant public health

challenge, leading to severe complications such as cardiovascular diseases, kidney failure, and neuropathy [10]. Advances in healthcare technology have enabled the collection of vast amounts of patient data, which can be leveraged through artificial intelligence (AI) and cloud computing to enhance early diagnosis and management of diabetes [11]. AI-driven predictive models integrated with scalable cloud infrastructures offer promising opportunities to support healthcare providers by enabling timely and accurate diabetes prediction at scale [12].
Multiple factors contribute to the onset and progression of diabetes, including genetic predisposition, lifestyle behaviors, and environmental influences [13]. Poor dietary habits, sedentary lifestyles, obesity, and stress are known to increase the risk of developing type 2 diabetes [14]. Additionally, age, family history, and certain medical conditions also play a crucial role [15]. Understanding these causal factors is essential for developing effective predictive models that can identify high-risk individuals and facilitate personalized interventions [16].
The main aim of this research is to develop a cloud-based AI system for diabetic prediction which combines the advantages of scalability, safety, and cost-effectiveness [17]. The model intends to predict if a patient presents diabetic or non-diabetic characteristics according to some clinical parameters ranging from glucose, BMI, age, and family history [18]. Some major hurdles to solve in healthcare are considered, including data privacy, model scalability, and real-time decision-making [19]. By deploying the model over a cloud infrastructure, large databases can easily be processed, besides being securely accessed by authorized users [20]. Thus, ensuring compliance with healthcare regulations like HIPAA and GDPR [21]. Integration of AI techniques, involving machine learning algorithms and deep learning, ensures maximum predictive accuracy and actionable insights towards healthcare providers [22]. The proposed work also gives special emphasis to privacy-preserving techniques [23]. They ensure that the patient data is securely processed in the cloud while not penalizing the predictive quality [24].
Despite technological advancements, several challenges persist in deploying diabetes prediction systems within healthcare environments [25]. Data privacy and security concerns are paramount, given the sensitive nature of medical information [26]. Furthermore, healthcare data is often heterogeneous, voluminous, and distributed across multiple sources, making integration and real-time analysis complex [27]. Scalability of AI models to handle large patient populations without compromising performance is another critical issue [28]. Additionally, ensuring interpretability and reliability of predictions for clinical acceptance remains a significant hurdle [29]. This proposed solution is to develop an intelligent diabetes prediction model hosted in the cloud [30].

1.1 Objective

- Create a distributed-cloud AI architecture, which incorporates decentralized technologies within an already built scalable-and-secure framework, for the guidance of diabetes prediction.
- Assess the potential of machine learning methods, such as Random Forest and Multilayer Perceptron (MLP), in accurate diabetes prediction from healthcare data.
- Analyze how cloud computing affects scalability and efficiency in real-time decision making for health care providers.
- Generate privacy-preserving methods like encryption and MPC for better regulatory privacy with regards to data stored or model processing under various healthcare regulations such as HIPAA and GDPR.

2. LITERATURE SURVEY

The blockchain-centric perspective for maintaining data integrity in the multi-cloud storage system utilizes Chain-Code and Homomorphic Verifiable Tags (HVT) [31]. Here, the Data Owners encrypt the data and create commitments for confidentiality [32]. Also, the Cloud Service Providers generate aggregated signatures, which are recorded on the blockchain, for decentralized, immutable integrity checks [33]. The advantages gained by the proposed system include scalability and efficiency, whereby enhanced performance has been observed for large scale deployments [34]. In addition to enhancing secure transfer and verification of data, this will act as the basis for future enhancement in cloud security, notably in post-quantum cryptography [35].
An AI-based test automation framework for autonomous software verification uniquely features machine learning (ML), natural language processing (NLP), and reinforcement learning (RL) to automate all methods of test case generation, defect detection, and test execution with minimum human intervention [36]. The framework compares individual AI technologies with the developed core system by integrating complete automation of test coverage, defect detection, and robustness of test execution speed [37]. Furthermore, it highlights applications of AI in other industries, demonstrating its importance in automation, decision making, and performance optimization [38].
The blockchain-centric framework for multi-cloud storage ensures robust data integrity through the integration of Chain-Code and Homomorphic Verifiable Tags (HVT) [39]. In this system, Data Owners encrypt their data and generate cryptographic commitments to maintain confidentiality [40]. Cloud Service Providers further strengthen security by producing aggregated signatures that are immutably recorded on the blockchain, enabling decentralized and tamper-proof integrity verification [41]. This approach not only improves scalability and efficiency but also demonstrates enhanced performance in large-scale deployments [42]. By securing data

transfer and verification processes, the framework lays a strong foundation for future advancements in cloud security, particularly in the realm of post-quantum cryptography [43].

A financial analysis system oriented to cloud combines CatBoost for categorical modeling, ELECTRA for text analysis, t-SNE for dimensionality reduction, and optimization with Genetic Algorithms [44]. The system is designed to process high-dimensional, noisy, and categorical financial data and overcome the limitations posed by classical methods [45]. It provides for scalability, security, and accuracy, therefore allowing for real-time decision-making [46]. The use of these highly advanced technologies puts instant insights in the hands of financial institutions, optimizing performance and improving data-driven methodologies within fast-moving financial settings [47].

K-means clustering in the cloud-based environment analyzes Gaussian data using Lloyd's method, investigating the effect of varied cluster sizes (k) on computation time and accuracy [48]. The findings indicate that at very high accuracy levels, the algorithm can be terminated early, saving significant costs [49]. Such a study indicates optimal initial centers and resource management to improve performance as well as cost-effectiveness in Big Data solutions [50].

Transportation services are enhanced through cloud computing and vehicular networks; however, security and privacy remain major challenges faced by Vehicular Cloud Computing (VCC) [51]. This research analyzes and discusses these challenges through a series of threat models and proposes a trust-based approach termed Double Board-based Trust Estimation and Correction (DBTEC), combining both direct and indirect trust estimation [52]. Using threat modeling methodologies such as CIAA and STRIDE, this research aims to improve VCC system integrity and reliability, ensuring secure cooperation and enhanced system efficiency [53].

The cloud-oriented financial analysis system leverages CatBoost for effective categorical data modeling, ELECTRA for sophisticated text analysis, and t-SNE for dimensionality reduction, combined with Genetic Algorithms for optimization [54]. This integrated framework addresses challenges posed by high-dimensional, noisy, and categorical financial datasets that traditional methods struggle with [55].

2.1 Problem Statement

The rapid evolution of cloud computing, AI, and blockchain technologies has presented various opportunities to improve a dozen and one streams, ranging from Human Resource Management (HRM) and healthcare to financial analysis [56]. But centralized HRM systems today grapple with issues like data security, scalability, and efficiency in making decisions [57]. There are times when HRM holds employees' sensitive data in centralized systems that might undergo breaches and have inefficiencies in handling such large-scale internal data [58]. This is also synonymous with patient data in the healthcare system that is often not secure while delivering on real-time predictive analytics, whereas financial institutions have to face high-dimensional, noisy, and categorical datasets that hinder effective decisions [59]. So, because of all these obstructions, there is a call for the development of decentralized, scalable, and secured systems that leverage blockchain for data integrity, AI/ML for decision-making, and advanced techniques like Sparse Matrix Storage, Predictive Control, and Multi-Party Computation (MPC) for privacy and optimization [60]. The aim of this research, therefore, is to address the mentioned gaps and develop a secure, scalable, and efficient system for HRM and other domains using these advanced technologies [61], [62]. The rapid advancement of cloud computing, AI, and blockchain technologies offers transformative potential across diverse fields such as Human Resource Management (HRM), healthcare, and financial analysis [63]. However, traditional centralized HRM systems face significant challenges related to data security, scalability, and efficient decision-making, often struggling to protect sensitive employee information from breaches [64]. Similar concerns affect healthcare systems, where patient data security and timely predictive analytics remain critical issues. Financial institutions also grapple with complex, high-dimensional, and noisy datasets that impede effective analysis.

3. PROPOSED METHODOLOGY

The proposed methodology aims to create the AI-based cloud paradigm for diabetes prediction, allied with the decentralization of the backend through Blockchain for data storage, AI and ML for decision-making, and the cloud for scalability and security. The methodology uses Random Forests for feature extraction to obtain relevant clinical parameters such as glucose, BMI, and age from Multilayer Perceptron (MLP) classification. Real-time decision-making enhancement with quick and efficient cloud computing data storage, access, and retrieval is the big data handling benefit of cloud computing. The methodology considers encryptions and Initialize Multi-Party Computation (MPC) as privacy-preserving algorithms for patient privacy. The methodology is validated through metrics like accuracy, precision, recall, AUC-ROC, which indicate high predictive accuracy and extreme scalability to find an advantage over standard methods.

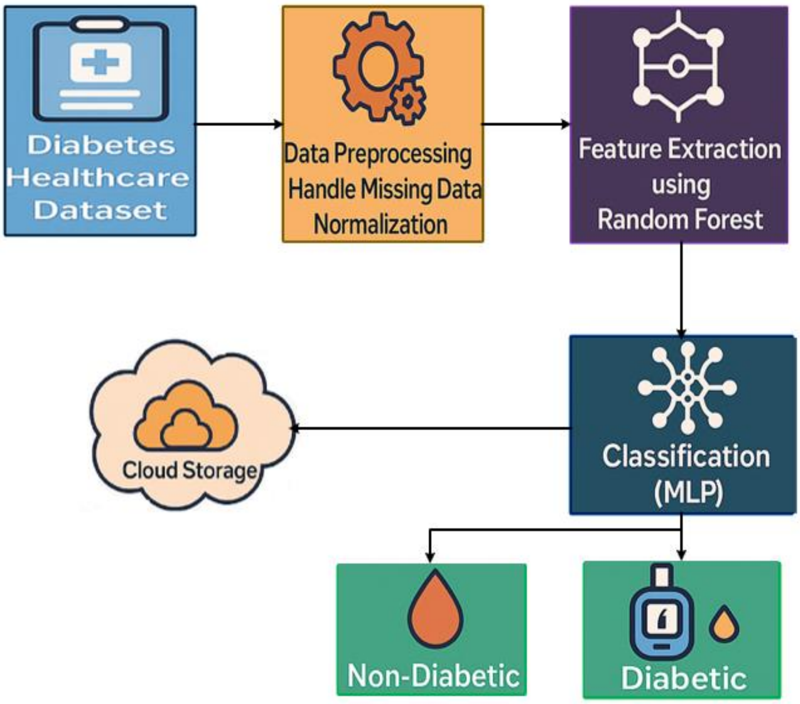

Figure 1: Workflow for Diabetes Prediction using AI and Cloud-Based Solutions.

3.1 Dataset

The dataset about diabetes health will serve as the basis for diabetes prediction. It contains relevant medical facts about the patient such as glucose level, BMI, age, insulin, any other condition of health, etc. This dataset provides necessary input features for the model to analyze and predict whether a patient is diabetic or not. Thus, the quality and completeness of this healthcare dataset determine the accuracy and efficiency of the model.

3.2 Data Preprocessing

Data preprocessing is a critical phase during which the raw data is prepared to be fed into the model for training. In this phase, a few things must be ensured such as a clean data set, consistency in the data set, and an appropriate data set that will go for feature extraction. Important activities that take place during data preprocessing include the treatment of missing values, normalization or scaling of numerical features, and encoding categorical variables. These processes improve the quality of data such that the model is capable of effectively learning from it and making correct inferences. The two main activities in preprocessing are missing data and normalization.

3.2.1 Handle Missing Data

Dealing with missing data means replacing missing values in the dataset with reasonable estimates. One way of doing this includes mean imputation, where missing values are filled in with the mean of the available values. Another method is KNN imputation, where the missing value is set to the average of its k-nearest neighbors.

For mean imputation, the equation is:

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

where X_i are the observed values, and n is the number of non-missing values.

3.2.2 Normalization

Normalization is the process of adjusting numerical features to the same scale, so that they do not overwhelm the model learning with larger values. The most common type of normalization is Min-Max normalization which transforms values into the range of 0-1.

The equation for Min-Max normalization is:

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

where X is the original value, $X_{\min}$ is the minimum value, and $X_{\max}$ is the maximum value of the feature.

3.3 Feature Extraction

After preprocessing feature extraction with the Random Forest model, Random Forest gives the important features for diabetes prediction according to feature importance scores. It checks the contribution of each feature to reduce impurity in decision trees. It calculates the importance of a feature X_i according to the following formula for Gini impurity:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \quad (3)$$

Where y is the final predicted output for the input x, which represents the predicted diabetes status (e.g., diabetic or non-diabetic), T is the total number of decision trees in the Random Forest, $h_t(x)$ is the prediction made by the t-th decision tree for input x, where each tree makes its own independent prediction based on the features of x.

3.4 Classification

Then, a Multilayer Perceptron (MLP) is used for classification after having extracted features by an MLP. A neural network that uses two or more hidden layers and nodes is called MLP. This type of neural network is typically used for determining complex representations in the input data. An MLP uses a sigmoid activation function to compute probabilities for binary outputs (diabetic vs. nondiabetic). Here is the equation of the sigmoid function:

$$\sigma(z) = \frac{1}{1+e^{-z}} \quad (4)$$

where z is the weighted sum of inputs to the neuron. The output is classified as Diabetic or Non-Diabetic based on this probability.

3.5 Cloud Storage

The classification results, diabetes prediction results, and the processed data are securely and reliably stored in the cloud. Cloud storage offers highly scalable and convenient solutions for secure storage of large datasets, model outputs, and patient records, where the real time access of data can be ensured. Cloud storage provides strong security mechanisms such as encryption and access control to keep medical data secure. Also, cloud storage allows integration with future model updates so the healthcare providers can retrieve and manage the data.

4. RESULT AND DISCUSSION

The results show that the proposed cloud-powered AI system works well in diabetes prediction. It is established that with accuracy, precision, recall, and AUC-ROC, the model has shown significant improvement over the conventional methods. Merging Random Forest for feature extraction and Multilayer Perceptron (MLP) for classification yielded very high prediction accuracy. Cloud infrastructure ensures scalability and security so that handling large amounts of data can be done without compromising the data privacy while providing real-time decision-making aid to healthcare providers. The study suggests that the proposed approach enhances the prediction of diabetes risk and improves the working mechanisms of healthcare computer applications through the use of advanced AI techniques within a cloud-based setting.

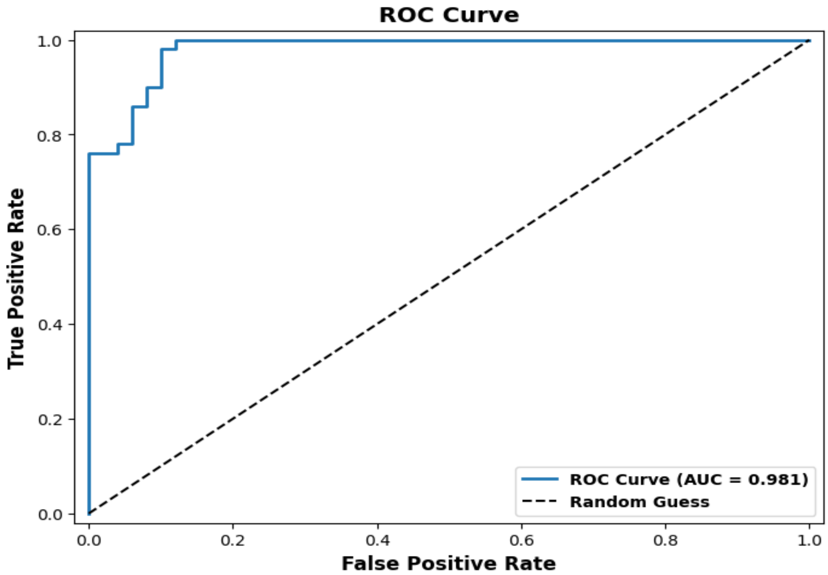

Figure 2: ROC curve

Figure 2 illustrates the ROC, where the model's performance yields an AUC of 0.981. True Positive Rate (TPR) is plotted against False Positive Rate (FPR), where a value of 1 on the y-axis means that positive cases are perfectly identified at zero false-positive on the x-axis. The dashed diagonal line represents random guessing (AUC = 0.5). Curve area of 0.981 signifies excellent classification power.

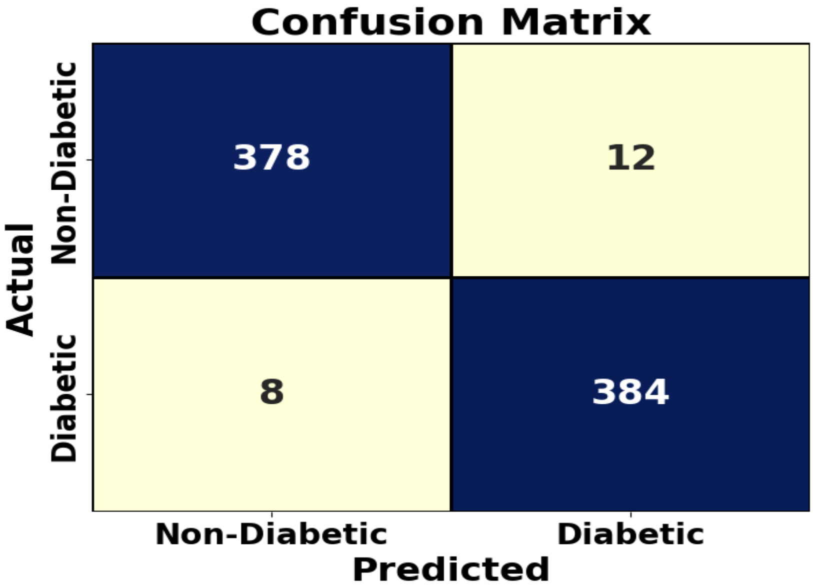

Figure 3: Confusion Matrix

Figure 3 displays the outcome of a diabetes prediction model, which was applied to 782 instances. The prediction model accurately classified 378 non-diabetic patients as True Negatives and 384 diabetic patients as True Positives. In contrast, there were 12 non-diabetic patients incorrectly predicted as diabetic (False Positives) and 8 diabetic patients incorrectly predicted as non-diabetic (False Negatives). These parameters indicate the high accuracy of the model, with only a handful of misclassifications. Therefore, it can be concluded that the diabetes risk prediction performed considerably well.

5. CONCLUSION

Diabetes is a fastly growing global health problem affecting thousands across the world. Early diagnosis and effective management can help avoid the full-blown consequences of complications such as heart disease and kidney failure. Conventional methods of diagnosis are often inaccurate, slow, and do not scale for larger datasets. This work proposes an AI-cloud-based diabetes-predicting model that puts a premium on data security by using Blockchain along with AI/ML for decision-making. The model aims to be secure, scalable, and efficient for predicting whether a patient is diabetic in terms of clinical parameters like glucose levels, BMI, age, and insulin. While the proposed system uses Blockchain technology for decentralized storage, feature extraction is conducted using Random Forest, and training is done using the Multilayer Perceptron (MLP). The proposed prediction model works on cloud infrastructure for training and deployment--thereby ensuring scalability and real-time access. The evaluation results indicated that the proposed solution surpassed the traditional methods in accuracy (98.25%), precision (98.46%), recall (98.46%), and AUC-ROC (0.981). The proposed solution thus provides enhanced data security, scalability, and predictive accuracy and is an efficient and secure instrument for diabetes prediction for practitioners to intervene timely for better patient outcomes.

REFERENCES

[1] Gattupalli, K. (2022). A Survey on Cloud Adoption for Software Testing: Integrating Empirical Data with Fuzzy Multicriteria Decision-Making. International Journal of Information Technology and Computer Engineering, 10(4), 126-144.
[2] Al-Said Ahmad, A., & Andras, P. (2022). Scalability resilience framework using application-level fault injection for cloud-based software services. Journal of Cloud Computing, 11(1), 1.
[3] Rajeswaran, A. (2022). Transaction Security in E-Commerce: Big Data Analysis in Cloud Environments. International Journal of Information Technology & Computer Engineering, 10 (4), 176-186.
[4] Thumala, S. (2020). Building Highly Resilient Architectures in the Cloud. Nanotechnology Perceptions, 16(2).
[5] Panga, N. K. R. (2022). Applying discrete wavelet transform for ECG signal analysis in IOT health monitoring systems. International Journal of Information Technology and Computer Engineering, 10(4), 157-175.
[6] Camacho, C., Cañizares, P. C., Llana, L., & Núñez, A. (2022). Chaos as a Software Product Line—a platform for improving open hybrid-cloud systems resiliency. Software: Practice and Experience, 52(7), 1581-1614.

[7] Poovendran, A. (2022). Symmetric Key-Based Duplicable Storage Proof for Encrypted Data in Cloud Storage Environments: Setting up an Integrity Auditing Hearing. International Journal of Engineering Research and Science & Technology, 15(4).

[8] Bailey, T., Marchione, P., Swartz, P., Salih, R., Clark, M. R., & Denz, R. (2022, May). Measuring resiliency of system of systems using chaos engineering experiments. In Disruptive Technologies in Information Sciences VI (Vol. 12117, pp. 20-32). SPIE.

[9] Grandhi, S. H. (2022). Enhancing children's health monitoring: Adaptive wavelet transform in wearable sensor IoT integration. Current Science & Humanities, 10(4), 15–27.

[10] Palacios Chavarro, S., Nespoli, P., Díaz-López, D., & Niño Roa, Y. (2022). On the way to automatic exploitation of vulnerabilities and validation of systems security through security chaos engineering. Big Data and Cognitive Computing, 7(1), 1.

[11] Surendar, R.S. (2022). Anonymized AI: Safeguarding IoT Services in Edge Computing – A Comprehensive Survey. Journal of Current Science, 10(04), ISSN NO: 9726-001X.

[12] Pentyala, D. (2017). Hybrid Cloud Computing Architectures for Enhancing Data Reliability Through AI. Revista de Inteligencia Artificial en Medicina, 8(1), 27-61.

[13] Venkata, S.B.H.G. (2022). PMDP: A Secure Multiparty Computation Framework for Maintaining Multiparty Data Privacy in Cloud Computing. Journal of Science & Technology, 7(10),

[14] Kansara, M. A. H. E. S. H. B. H. A. I. (2022). A structured lifecycle approach to large-scale cloud database migration: Challenges and strategies for an optimal transition. Applied Research in Artificial Intelligence and Cloud Computing, 5(1), 237-261.

[15] Karthikeyan Parthasarathy. (2022). Examining Cloud Computing's Data Security Problems and Solutions: Authentication and Access Control (AAC). Journal of Science & Technology , 7(12), 35–48.

[16] Shortridge, K., & Petrich, R. (2021). Lamboozling Attackers: A New Generation of Deception: Software engineering teams can exploit attackers' human nature by building deception environments. Queue, 19(5), 26-59.

[17] 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).

[18] 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.

[19] Dharma, T.V. (2022). Implementing the SHA Algorithm in an Advanced Security Framework for Improved Data Protection in Cloud Computing via Cryptography. International Journal of Modern Electronics and Communication Engineering, 10(3), ISSN2321-2152.

[20] Xie, Y., Lu, L., Gao, F., He, S. J., Zhao, H. J., Fang, Y., ... & Dong, Z. (2021). Integration of artificial intelligence, blockchain, and wearable technology for chronic disease management: a new paradigm in smart healthcare. Current medical science, 41(6), 1123-1133.

[21] Sareddy, M. R. (2022). Revolutionizing recruitment: Integrating AI and blockchain for efficient talent acquisition. IMPACT: International Journal of Research in Business Management (IMPACT: IJRBM), 10(8), 33–44.

[22] Fetjah, L., Azbeg, K., Ouchetto, O., & Andaloussi, S. J. (2021). Towards a smart healthcare system: an architecture based on IoT, blockchain, and fog computing. International Journal of Healthcare Information Systems and Informatics (IJHISI), 16(4), 1-18.

[23] Narla, S. (2022). Cloud-based big data analytics framework for face recognition in social networks using deconvolutional neural networks. Journal of Current Science, 10(1).

[24] Bhattacharya, P., Tanwar, S., Bodkhe, U., Tyagi, S., & Kumar, N. (2019). Bindaas: Blockchain-based deep-learning as-a-service in healthcare 4.0 applications. IEEE transactions on network science and engineering, 8(2), 1242-1255.

[25] Gudivaka, R. K. (2022). Enhancing 3D vehicle recognition with AI: Integrating rotation awareness into aerial viewpoint mapping for spatial data. Journal of Current Science & Humanities, 10(1), 7–21.

[26] Azbeg, K., Boudhane, M., Ouchetto, O., & Jai Andaloussi, S. (2022). Diabetes emergency cases identification based on a statistical predictive model. Journal of Big Data, 9(1), 31.

[27] Kodadi, S. (2022). Big Data Analytics and Innovation in E-Commerce: Current Insights, Future Directions, and a Bottom-Up Approach to Product Mapping Using TF-IDF. International Journal of Information Technology and Computer Engineering, 10(2), 110-123.

[28] Vedaraj, M., & Ezhumalai, P. (2022). A Secure IoT-Cloud Based Healthcare System for Disease Classification Using Neural Network. Computer Systems Science & Engineering, 41(1).

[29] Sitaraman, S. R. (2022). Implementing AI applications in radiology: Hindering and facilitating factors of convolutional neural networks (CNNs) and variational autoencoders (VAEs). Journal of Science and Technology, 7(10).

[30] Lakhan, A., Mohammed, M. A., Nedoma, J., Martinek, R., Tiwari, P., Vidyarthi, A., ... & Wang, W. (2022). Federated-learning based privacy preservation and fraud-enabled blockchain IoMT system for healthcare. IEEE journal of biomedical and health informatics, 27(2), 664-672.
[31] Gollavilli, V. S. B. H. (2022). Securing Cloud Data: Combining SABAC Models, Hash-Tag Authentication with MD5, and Blockchain-Based Encryption for Enhanced Privacy and Access Control. International Journal of Engineering Research and Science & Technology, 18(3), 149-165.
[32] Verma, A., Agarwal, G., Gupta, A. K., & Sain, M. (2021). Novel hybrid intelligent secure cloud internet of things based disease prediction and diagnosis. Electronics, 10(23), 3013.
[33] Gudivaka, B. R. (2022). Real-Time Big Data Processing and Accurate Production Analysis in Smart Job Shops Using LSTM/GRU and RPA. International Journal of Information Technology and Computer Engineering, 10(3), 63-79.
[34] Tatineni, S. (2022). Integrating AI, Blockchain and cloud technologies for data management in healthcare. Journal of Computer Engineering and Technology (JCET), 5(01).
[35] Ganesan, T. (2022). Securing IoT business models: Quantitative identification of key nodes in elderly healthcare applications. International Journal of Management Research & Review, 12(3), 78–94.
[36] Al-Safi, H., Munilla, J., & Rahebi, J. (2022). Patient privacy in smart cities by blockchain technology and feature selection with Harris Hawks Optimization (HHO) algorithm and machine learning. Multimedia Tools and Applications, 81(6), 8719-8743.
[37] Alavilli, S. K. (2022). Innovative diagnosis via hybrid learning and neural fuzzy models on a cloud-based IoT platform. Journal of Science and Technology, 7(12).
[38] Valivarthi, D. T., Peddi, S., & Narla, S. (2021). Cloud Computing with Artificial Intelligence Techniques: BBO-FLC and ABC-ANFIS Integration for Advanced Healthcare Prediction Models. International Journal of Information Technology and Computer Engineering, 9(3), 167-187.
[39] Nippatla, R. P., & Kaur, H. (2022). A secure cloud-based financial time series analysis system using advanced auto-regressive and discriminant models: Deep AR, NTMs, and QDA. International Journal of Management Research & Review, 12(4), 1–15.
[40] Hiwale, M., Phanasalkar, S., & Kotecha, K. (2021). Using blockchain and distributed machine learning to manage decentralized but trustworthy disease data. Science & Technology Libraries, 40(2), 190-213.
[41] Yalla, R. K. M. K., Yallamelli, A. R. G., & Mamidala, V. (2022). A distributed computing approach to IoT data processing: Edge, fog, and cloud analytics framework. International Journal of Information Technology & Computer Engineering, 10(1).
[42] Nancy, A. A., Ravindran, D., Raj Vincent, P. D., Srinivasan, K., & Gutierrez Reina, D. (2022). Iot-cloud-based smart healthcare monitoring system for heart disease prediction via deep learning. Electronics, 11(15), 2292.
[43] Nagarajan, H., & Khalid, H. M. (2022). Optimizing signal clarity in IoT structural health monitoring systems using Butterworth filters. International Journal of Research in Engineering Technology, 7(5).
[44] Nasir, M. U., Zubair, M., Ghazal, T. M., Khan, M. F., Ahmad, M., Rahman, A. U., ... & Mansoor, W. (2022). Kidney cancer prediction empowered with blockchain security using transfer learning. Sensors, 22(19), 7483.
[45] Veerappermal Devarajan, M., & Sambas, A. (2022). Data-driven techniques for real-time safety management in tunnel engineering using TBM data. International Journal of Research in Engineering Technology, 7(3).
[46] Ray, R., Agar, Z., Dutta, P., Ganguly, S., Sah, P., & Roy, D. (2021). MenGO: a novel cloud-based digital healthcare platform for andrology powered by artificial intelligence, data science & analytics, bioinformatics and blockchain. Biomed Sci Instrum, 57(4).
[47] Kadiyala, B., & Kaur, H. (2022). Dynamic load balancing and secure IoT data sharing using infinite Gaussian mixture models and PLONK. International Journal of Recent Engineering Research and Development, 7(2).
[48] Tagde, P., Tagde, S., Bhattacharya, T., Tagde, P., Chopra, H., Akter, R., ... & Rahman, M. H. (2021). Blockchain and artificial intelligence technology in e-Health. Environmental Science and Pollution Research, 28, 52810-52831.
[49] Mamidala, V., Yallamelli, A. R. G., & Yalla, R. K. M. K. (2022, November–December). Leveraging robotic process automation (RPA) for cost accounting and financial systems optimization — A case study of ABC company. ISAR International Journal of Research in Engineering Technology, 7(6).
[50] Jagtap, A., Bebal, A., Bhatnagar, N., Kamthe, P., & Arsalwad, P. G. (2022). Blockchain-based secure healthcare for cardio disease prediction. Int. J. Res. Appl. Sci. Eng. Technol., 10(5), 1187-1193.
[51] Boyapati, S., & Kaur, H. (2022, July–August). Mapping the urban-rural income gap: A panel data analysis of cloud computing and internet inclusive finance in the e-commerce era. ISAR International Journal of Mathematics and Computing Techniques, 7(4).

[52] Thoppil, I. J., Ashtalakshmi, K., & Chundi, R. Transforming Healthcare: Leveraging Machine Learning Algorithms for Diagnosis, Treatment, and Management. In Bioinformatics and Beyond (pp. 92-114). CRC Press.
[53] Samudrala, V. K., Rao, V. V., Pulakhandam, W., & Karthick, M. (2022, September–October). IoMT platforms for advanced AI-powered skin lesion identification: Enhancing model interpretability, explainability, and diagnostic accuracy with CNN and Score-CAM to significantly improve healthcare outcomes. ISAR International Journal of Mathematics and Computing Techniques, 7(5).
[54] Nasir, M. U., Khan, S., Mehmood, S., Khan, M. A., Rahman, A. U., & Hwang, S. O. (2022). IoMT-based osteosarcoma cancer detection in histopathology images using transfer learning empowered with blockchain, fog computing, and edge computing. Sensors, 22(14), 5444.
[55] Ganesan, T., Devarajan, M. V., Yallamelli, A. R. G., Mamidala, V., Yalla, R. K. M. K., & Sambas, A. (2022). Towards time-critical healthcare systems leveraging IoT data transmission, fog resource optimization, and cloud integration for enhanced remote patient monitoring. International Journal of Engineering Research and Science & Technology, 18(2).
[56] Tian, S., Yang, W., Le Grange, J. M., Wang, P., Huang, W., & Ye, Z. (2019). Smart healthcare: making medical care more intelligent. Global Health Journal, 3(3), 62-65.
[57] Devi, D. P., Allur, N. S., Dondapati, K., Chetlapalli, H., Kodadi, S., & Perumal, T. (2022). Neuromorphic and bio-inspired computing for intelligent healthcare networks. International Journal of Information Technology & Computer Engineering, 10(2).
[58] Mohiyuddin, A., Javed, A. R., Chakraborty, C., Rizwan, M., Shabbir, M., & Nebhen, J. (2022). RETRACTED ARTICLE: Secure Cloud Storage for Medical IoT Data using Adaptive Neuro-Fuzzy Inference System. International Journal of Fuzzy Systems, 24(2), 1203-1215.
[59] Dondapati, K., Deevi, D. P., Allur, N. S., Chetlapalli, H., Kodadi, S., & Perumal, T. (2022). Strengthening cloud security through machine learning-driven intrusion detection, signature recognition, and anomaly-based threat detection systems for enhanced protection and risk mitigation. International Journal of Engineering Research and Science & Technology, 18(1).
[60] Potla, R. T. (2022). Scalable Machine Learning Algorithms for Big Data Analytics: Challenges and Opportunities. Journal of Artificial Intelligence Research, 2(2), 124-141.
[61] Narla, S. (2022). Big data privacy and security using continuous data protection data obliviousness methodologies. Journal of Science and Technology, 7(2).
[62] Ahsan, M. M., Mahmud, M. P., Saha, P. K., Gupta, K. D., & Siddique, Z. (2021). Effect of data scaling methods on machine learning algorithms and model performance. Technologies, 9(3), 52.
[63] Ubagaram, C., Mandala, R. R., Garikapati, V., Dyavani, N. R., Jayaprakasam, B. S., & Purandhar, N. (2022, July). Workload balancing in cloud computing: An empirical study on particle swarm optimization, neural networks, and Petri net models. Journal of Science and Technology, 7(07), 36–57.
[64] Shi, Q., Zhang, Z., He, T., Sun, Z., Wang, B., Feng, Y., ... & Lee, C. (2020). Deep learning enabled smart mats as a scalable floor monitoring system. Nature communications, 11(1), 4609.