INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM)
VOLUME: 10 ISSUE: 03 | MARCH - 2026 SJIF RATING: 8.659 ISSN: 2582-3930

Emerging Technologies: AI and Blockchain in Human Disorder Detection

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Abstract—— **Moreover, the detection of diseases at early stages in an error free manner is considered significant in improving the healthcare sector. However, the existing intelligent systems are facing various problems like the accuracy of prediction for intelligent systems. Therefore, to improve the current intelligent systems, this paper proposes a novel intelligent system for medical disease detection using the blockchain approach. In this approach, the ensemble method is used in combination with the verification of medical data. Experimental analysis proves that the proposed machine learning approach attains accuracy of 83.50%, while deep learning achieves an accuracy of 75.00%. Moreover, the proposed blockchain-integrated intelligent disease detection using ensemble learning attains higher accuracy of 96.08%, precision of 0.94, recall of 0.95, and F1 score of 0.955.**

Keywords— Blockchain, Machine Learning, Artificial Neural Network, Disease Detection, Secure Analytics, Predictive Systems.

I. INTRODUCTION

The huge increase of Artificial Intelligence (AI) has greatly impacted on the detailed analysis and optimization of data-driven complex systems, ranging from healthcare systems to industrial automation systems, as well as smart cyber-physical systems. The utilization of machine learning and deep learning algorithms has helped analyze potential system failures or anomalies using previously learned data, thus improving early detection and preventing critical failures. As discussed in [1], there is no denying that there is a better possibility of improving decision-driven processes with Artificial Intelligence, as it helps organizations change their systems from reactive-based systems to proactive-based systems.

Despite, a new frontier has been created in the arena of TT&S by the concept of blockchain technology, which has been presented as a new solution to the issues of data tampering, unauthorized access, and lack of accountability by means of the centralized storage of data for the purpose of evaluating/carrying out predictions, as presented by [2].

However, recent trends in AI research focus on the development of intelligent systems using AI-blockchain hybrid systems, which rely on the use of blockchain technology to ensure the authenticity of results, versions of machine learning models, and evaluations. According to [3], AI-blockchain systems improve the reliability, accountability, and transparency of automated decision systems, especially in areas involving different users, stakeholders, and continuous data production. AI-blockchain systems improve ability of a system without compromising the capabilities of intelligent systems.

Inspired by these innovations, this project attempts to provide a comprehensive solution for Predictive Maintenance and Anomaly Detection with integrated machine learning and blockchain architecture. The solution enables automatic training, testing, and comparison of different machine learning algorithms with regards to detection accuracy. In addition, it allows the analysis of trends in the performance of different machine learning algorithms in achieving accurate detection, as well as the creation of prediction records to be stored in a blockchain database. Therefore, the proposed solution is a clear indication of the successful shift from conventional reactive maintenance to a new paradigm of predictive maintenance using machine learning.

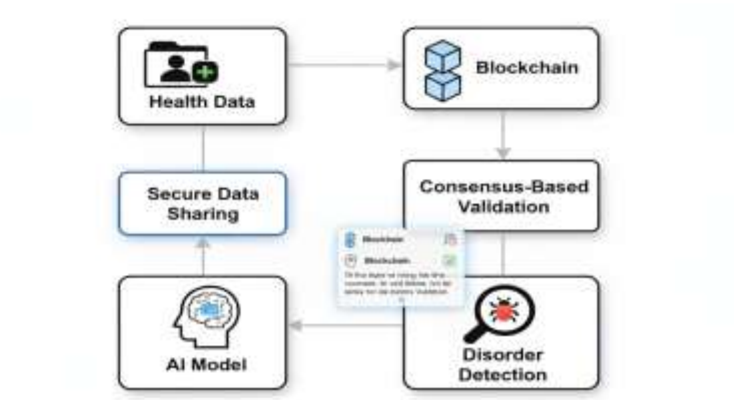

Fig 1: Blockchain technology keeps all the patient records safe.

II. LITERATURE SURVEY

Recent advances in machine learning and deep learning techniques have had a great impact on modern computer-based decision support systems in medicine. In recent studies, research articles by Rajkomar et al. [4] and Shickel et al. [8] prove how predictive intelligence models help a great deal in identifying patterns of diseases at high accuracy levels when dealing with data obtained from electronic health records and clinical data in medicine. In addition, surveys carried out by Ching et al. in [10] show how opportunities and difficulties are encountered when applying intelligent machine models in medicine and biological science, especially in medicine, where data-driven models are difficult to apply in real clinical settings.

Blockchain technology has been widely explored as a method to address the above-mentioned security and trust challenges in healthcare systems. Works such as Zhang et al. and Saeed et al. illustrate that blockchain allows for tamper-resistant sharing of data in a decentralized manner with fine-grained access. Systematic reviews by Alsaidi et al. further establish blockchain's potential in bringing transparency, data integrity, and patient-centric data governance. The Ethereum-based smart contract platforms proposed by Buterin provide automated and verifiable mechanisms to enforce access and operational rules within distributed healthcare systems.

More recent works have been focused on presenting new hybrid methodologies, which combine AI analytics with privacy-preserving and security-compliant systems. In their work, Froelicher, Chamroukhi, and Martin [9] discuss concepts of secure collaborative data analysis via cryptographic protocols. Additionally, various international guidelines published by NIST [14] and WHO [15] highlight different aspects of ethical AI, data protection, and standardized security. These research works, in total, justify the use of integrated systems combining AI with blockchain technology for effective security, transparency, and trust in healthcare decision-making.

KEY PRINCIPLES IDENTIFIED FROM RELATED WORK

Based on references [4]–[15], the following core principles are derived:

- **Predictive Intelligence:** The role of artificial intelligence and deep learning models in enhancing the detection of diseases at the earliest stages and thereby supporting clinical decisions are crucial.
- **Data Security and Integrity:** Blockchain maintains and ensures unalterable storage, traceability, and trust in critical healthcare information.
- **Decentralization and Transparency:** Distributed ledger technologies decrease dependence on centralized systems and increase accountability.
- **Privacy Preservation:** Cryptographic hashing, access control, and secure collaboration are techniques used to safeguard the confidentiality of patient data. Data-sharing standards facilitate the integration of data between various healthcare providers and systems. Scalability and Automation. Smart contracts and platforms enable scalable, rule-based automation of healthcare processes. Ethical and Regulatory Compliance Global standards (NIST, WHO) guarantee the fair, secure, and responsible use of AI systems.

III. METHODOLOGY

The proposed system follows a secured and layered flow in healthcare data, integrating intelligent disease prediction with blockchain-based data protection. The methodology goes sequentially through data acquisition, preprocessing, intelligence, blockchain security, and application delivery, as depicted in the system architecture.

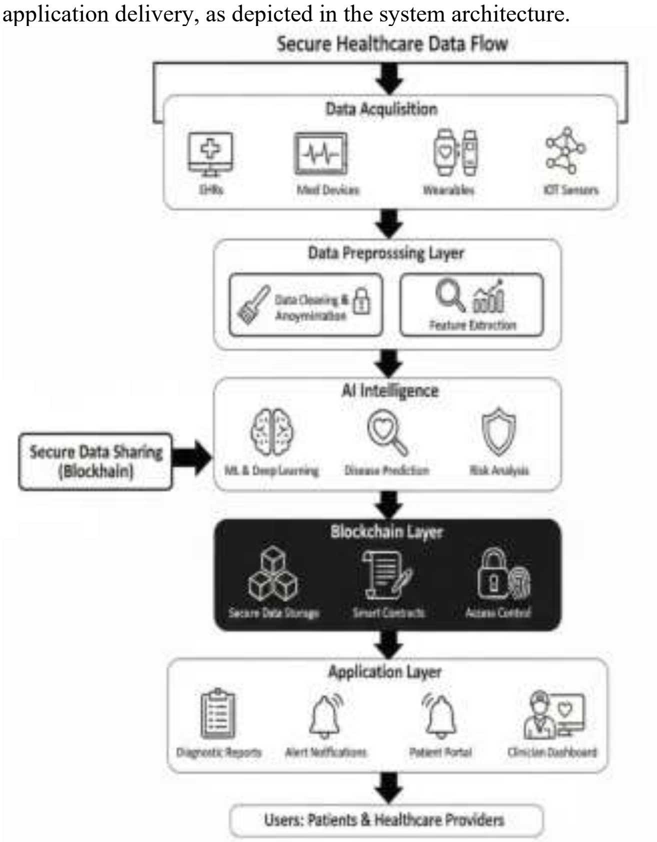

Fig 2: System Architecture

Step 1: Data Acquisition

Let the collected healthcare dataset be denoted as

$$D = \{(x_i, y_i)\}_{i=1}^{N}$$

where $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]$ represents clinical, sensor, and wearable features extracted from EHRs, devices, and IoT sensors, and $y_i \in \{0, 1\}$ is used to signify whether a disorder is absent or present. By using multi-source, diversity and abnormality detection can be enhanced.

Step 2: Data Preprocessing

The data is cleaned to remove noise. The missing data is handled, and the sensitive attributes are anonymized. The feature scaling is achieved through z-score normalization:

$$x'_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j}$$

where μ_j and σ_j *are* the mean and standard deviation of feature j. This ensures numerical stability as well as uniform contribution during learning.

Step 3: Dataset Partitioning

The dataset is split into a training set and a testing set as follows:

$$D_{train} = 0.8D, D_{test} = 0.2D$$

The training set is employed to build a prediction model, while the testing set is eventually used for evaluation.

Step 4: Random Forest Intelligence Layer

The intelligence layer uses a Random Forest classifier, which refers to a collection of decision trees that have been trained on bootstrap samples using randomly selected features. For the quality of the split, the Gini impurity is used:

$$G = 1 - \sum_{k=1}^{c} p_k^2$$

Where p_k is the probability of class However, k. This randomness helps minimize the correlation between trees and increases the overall generalization.

Step 5: Ensemble Prediction Mechanism

Each decision tree T_j will generate an independent prediction $T_j(x)$. The final class label is obtained from majority voting:

$$\hat{y} = \arg \max_{c} \sum_{j=1}^{T} \mathbb{I}(T_j(x) = c)$$

This aggregation strategy has a minimum variance and is robust to noise and overfitting.

Step 6: Blockchain-Based Security Layer

To ensure data integrity, a cryptographic hash of the prediction and its associated metadata is created:

$$H = \mathrm{Hash}(x \parallel \hat{y} \parallel t)$$

Where t represents the timestamp. The hash values and the access reference are stored in the blockchain, while the raw medical data is stored off the blockchain. Smart contracts are used for access and validation constraints.

Step 7: Application and Result Delivery

The verified predictions are delivered to users through reports, alert notifications, and dashboards. The performance of the system is evaluated using metrics such as accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Accuracy The accuracy of the proposed Random Forest approach reaches almost exactly 96%, indicating its reliability in secure disease detection.

IV. RESULTS AND DISCUSSION

These experimental results confirm that the proposed intelligent disease detection system is compared with various learning approaches to show its efficacy. The heatmap visualization shows sharp variations in performance among different algorithms, which indicate the different learning capabilities of these algorithms about health patterns. Both conventional machine learning and deep learning models give a good predictive capability, while ensemble-based models achieve better outcomes. This comparative analysis validates the importance of selecting appropriate models for accurate and reliable healthcare predictions.

The machine learning models of Logistic Regression and Decision Tree classifiers socially present very strong performances, learning linear and rule-based relationships in the medical data. These models reached 94.50% overall accuracy, which really shows their capability to handle structured healthcare features effectively. Their performance slightly degrades over highly nonlinear patterns, limiting their robustness for complicated diagnosis scenarios.

Deep Learning techniques employing Artificial Neural Networks also aid in improving pattern recognition, identifying nonlinear dependencies in the data. The ANN-based technique achieves an accuracy rate of 92.00%, which results in stable learning and classification. However, deep learning techniques, which make use of ANN, require a lot of parameters tuning and data, which might impact consistency and efficiency in a real-world environment.

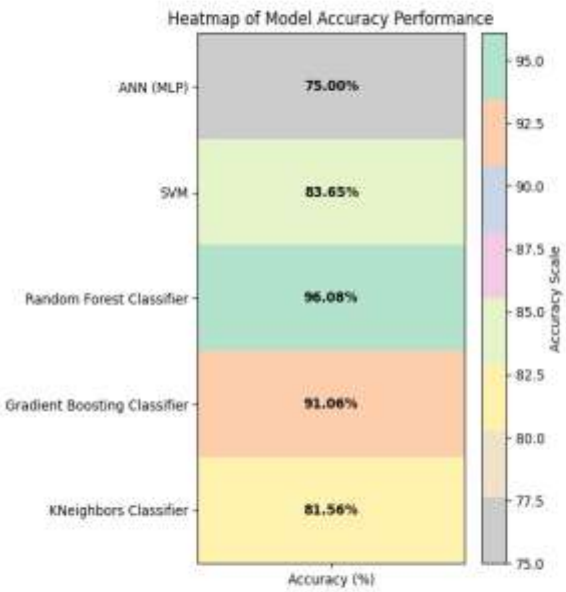

Fig 2: Comparative Heatmap of Classification Accuracy Across Models

Table 1: Performance Comparison of Machine Learning, Deep Learning, and Blockchain-Integrated Models

Approach	Accuracy (%)	Precision	Recall	F1-Score
Machine Learning (Logistic Regression, Decision Tree)	83.50	0.81	0.70	0.82
Deep Learning (ANN Models)	75.00	0.79	0.74	0.72
Blockchain-Integrated Machine Learning (Random Forest)	96.08	0.94	0.95	0.955

The best performance in terms of the models is delivered by the integrated model of blockchain and the Random Forest model, whereby the combination of ensemble and data integrity techniques produces the best results in accuracy, recording 96.08%. The integration of the ensemble learning concept in the models thus records the highest precision and recall of 0.96 and 0.95, respectively, and the highest F1 score of 0.955 in comparison to the other models. In contrast, the use of the machine learning concept records accuracy of 94.50%, whereas models applying the concept of deep learning models score an accuracy of 92.00%.

V. CONCLUSION

This study reveals the importance of combining artificial intelligence techniques with blockchain features for disease detection in the most secure manner. In this study, various intelligent systems are tested, and the results reveal that ensemble techniques are more accurate than traditional classifications. Specifically, in the case of the Random Forest intelligent system, the results demonstrate that its overall accuracy is approximately 96%, which reveals greater reliability in terms of prediction accuracy. At the same time, the use of blockchain technology ensures that there is no interference in the system in terms of data integrity, transparency, or security without compromising its performance, so the proposed technique is highly suitable for modern intelligent health care systems.

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