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IoT and AI-Driven Predictive Healthcare Systems: The Intersection of Machine Learning, Blockchain, and Healthcare Management Practices

Shaik Akbar[1], Venkata N Seerapu[2], Kiruthikka.D.C[3], M. Sivachitra[4], Sathish Kumar Shanmugam[5], Dr Kiran Kumar Reddy Penubaka[6]

[1]Designation:Assoc.Professor, Department:CSE(AI&ML), Institute:Geethanjali College of Engineering and Technology, District: Medchal, City:Hyderabad, State:Telangana.

Email ID: akbarshaik71185@gmail.com

[2]Designation: Clinical research Manager, Department: Department of Surgery, Institute: University of Mississippi Medical Center.

Email ID: vseerapu@umc.edu

[3]Designation: Assistant Professor, Department: Artificial Intelligence and Data Science, Institute: Dr. Mahalingam college of engineering and technology, District: Coimbatore, City: Pollachi, State: Tamilnadu

Email ID: kiruthikkadc@drmcet.ac.in

[4]Designation: Professor, Department: Electrical and Electronics Engineering, Institute: Kongu Engineering College, Perundurai, District:Erode, City: Perundurai, State: Tamilnadu

Email ID: siva.chitra3@gmail.com

[5]Designation: Associate Professor, Department: Electrical and Electronics Engineering, Institute:M.Kumarasamy College of Engineering,Karur, District:Karur, City: Karur, State: Tamilnadu

Email ID: sathishphd2k17@gmail.com

[6]Designation: Professor, Department: CSE-AIML, Institute: MLR Institute of technology, District: Medchal, City: Hyderabad, State: Telangana

Email ID: kiran.penubaka@gmail.com

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ABSTRACT

Artificial Intelligence (AI), Internet of Things (IoT), and Blockchain technologies are converging to shape predictive healthcare systems that are intelligent, secure and real time patient care. The main focus of this research is the integration of these technologies for enhanced predictive diagnostics, health monitoring and data management. Four machine learning algorithms i.e. Random Forest, Long Short Term Memory (LSTM), Support Vector Machine (SVM) and XGBoost are implemented and evaluated using real world healthcare datasets. Metrics such as accident prediction, accident Localiziation, accident Explanations and Dynamic Route Choice were measured as the performance of these models and as such, it was found out that Lstm had the highest accuracy of 96.8, XgBoost had achieved with 94.5, Random Forest with 92.3 and Support Vector Machine with 90.7. Results show that real time IoT data used along with Blockchain supported AI algorithms make early disease prediction and health trend analysis more accurate and efficient. It also increases data transparency and security, solving important issues of healthcare information systems. Further comparative analysis with related work confirms further that the proposed model has good precision, recall and data integrity. In this study, this framework demonstrates the practicality of techno-medical application for next generation of healthcare system, providing more proactive and personalized healthcare services.

Keywords: *Predictive Healthcare, Artificial Intelligence, Internet of Things, Blockchain, Machine Learning.*

1. INTRODUCTION

In spite of its accelerated development, technology is pushing ahead in healthcare sector as predictional health care systems are coming forward which plays a key role in patient’s outcoming management, in saving money and efficient in care delivery. The most significant technological enablers are Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML) and Blockchain. This convergence provides an opportunity to create intelligent, secure and scalable healthcare systems that can anticipate health issues before these become critical and shift the focus from reactive to proactive care [1]. Continuously, these data can come from IoT devices like wearable sensors, smart monitors, connected medical equipment in order to reflect the realtime physiological and behavioral results. This data, combined with AI and ML algorithms, can be processed to detect patterns, predict disease progression and personalize treatment [2]. ML powered predictive analytics help in early diagnosis, the timely interventions, and advance patient monitoring, which enhances patient care quality to a great extent. But the level of sensitivity of the health data collected by IoT devices is growing, and as such, concerns over data privacy, data security, and data integrity have greater implications [3]. However, blockchain technology offers a solution to these challenges through a decentralized and tamper proof method of storing and sharing medical data securely. Better Healthcare Systems can be realized as blockchain integrated with AI and IoT for data trustworthiness, patient consent management and regulatory compliance. In this research, the integration of IoT, AI and Machine learning and blockchain with predictive healthcare systems used is explored. It considers how the healthcare management practices can be implemented with the use of these technologies to enhance service delivery, data security, and decision making process. Through an in depth analysis, the study sets out to give some answers to the practical implementation of such systems as well as their effects on the level of efficiency of the healthcare, as well as on patient's outcomes and organisational performance. Overall, this research enables the development of smarter, safer and more preditive healthcare ecosystems.

2. RELATED WORKS

Artificial Intelligence is a disruptive force, a powerful game that is transforming the processes and actually automating, the analytics and the decision making smarter. There are several studies reported on the integration of artificial intelligence across various lifecycle of industrial systems. Elahi et al. [15] had conducted a comprehensive literature review on the use of AI techniques in monitoring, diagnosis, and predictive maintenance in the lifecycle of the industrial equipment. The findings, they add, only underline the increasing applicability of AI in the enhancement of operational efficiency and reduction of equipment downtime. Integrating IoT with AI has enabled the make-up of precision agriculture within the agricultural domain. Elikem Elisha et al. [16] examined how there are ways AI technologies can incorporate the implementation of resource optimizing and crop monitoring through IoT frameworks. Mohammed Aarif et al. [26] also reviewed the smart sensor technology advancement progress for the precision agriculture and predicted a future where autonomous sensors will ultimately provide AI-mediated guidance for irrigation, fertilisation, and the harvesting based with minimum human help.

In the realm of urban infrastructure and development, AIʹs contribution to building intelligent buildings and cities is becoming more prominent. Emad et al. [17] also looked into the use of AI to create future intelligent tall buildings that are environmentally sound, manage energy, and have adaptive architecture. In his systematic review on the cognitive predictive maintenance of urban assets with the use of AI enabled CIM City Information Modeling [21], Lawal et al. emphasized the contribution of intelligent systems in the management of the lifecycle of the urban infrastructure assets more efficiently. On the other hand, the role of AI in financial innovation is also notable. AI and related technologies, Garad et al. [18] argued, can be used to strategically manage information to promote financial innovation through better investment choices, risk analysis and customer services automation. Additionally, Karim et al. [19] also taken up the study of how can AI agents, along with blockchain, lead to scalab性 and secure way of collaboration of multi?agent systems specially in finance and supply chain applications. Research in AIʹs convergence with other emerging technologies has also been carried out. Kulkov et al. [20] investigated whether AI is more effective when it operates on its own or when combined with another technology like blockchain, IoT, robotics etc. According to their research, the superior outcomes that result from synergistic integration happen mostly in innovation drive industries. Miller et al. [25] have demonstrated this integrative potential in which AI agents working in conjunction with IoT can enhance environmental monitoring, particularly in water quality and climate data analysis, to a great extent.

From the AI, the metaverse is being reimagined. Lifelo et al. [22] studied the employment of the AI metaverse environments in sustainable smart cities. Through their study, they identify technologies and applications that enable AI to boost immersive virtual experiences, smart governance and urban sustainability, but also interested challenges, like gaining data and ethical issues, for example. López-Meneses et al. [23] did apply the use of AI within the field of education in educational data mining and predictive modeling. The implications of their work highlight the extent to which AI is changing the face of learning analytics, including possible institution-wide personalization of education and better prediction of student outcomes. Mehmood et al. [24] focused on healthcare and rehabilitation as well, and they surveyed such AI powered tools for current patient care. The most exciting next generation innovations that they cover in the research include intelligent prosthetics, AI based physiotherapy guidance and remote health monitoring systems.

All together, these studies show that AI is a versatile tool capable of being applied to every domain from agriculture and education to smart cities and healthcare. AI has been integrated with other technologies such as IoT, blockchain, CIM, in order to have more intelligent, responsive and sustainable systems. The literature shows a lot of progress, but also a number of remaining issues with respect to the ethical implementation, data privacy, interoperability and the long term scalability. To unlock the true power of AI in practical use cases, some of these problems will need to be resolved.

3. METHODS AND MATERIALS

3.1 Data Collection and Preprocessing

The data for this study were collected from an open-source IoT-based healthcare dataset with real-time physiological data. It comprises features such as heart rate, oxygen saturation, body temperature, ECG signals, glucose, and activity status [4]. The dataset is a representative of continuous monitoring with wearable sensors. For this study, 10,000 patient records were used, each with 12 features and a binary target variable indicating whether the patient has a chance of developing a critical condition in the next 24 hours [5].

The information went through preprocessing procedures:

- Handling missing values with K-nearest neighbors (KNN) imputation
- Scaling sensor reading by min-max scaling
- Encoding category variables (e.g., activity level)
- Partitioning the data into test (30%) and training (70%) sets

3.2 Algorithms Used in Predictive Modeling

In order to analyze and predict healthcare conditions from the IoT dataset, four widely used machine learning algorithms were used and compared:

1. Random Forest Classifier

Random Forest is an ensemble learning technique in which several decision trees are trained during training and the class that is the mode of the classes (classification) of the individual trees is predicted. Random Forest operates on large datasets with higher dimensionality and avoids overfitting by averaging numerous models [6]. Each tree is trained on a bootstrap sample of the dataset and features are selected randomly at each node so that there is model diversity. Random Forest is very strong in predictive healthcare to detect patterns in physiological data for risk prediction. It gives robust performance even with noisy or missing data and performs best in real-world IoT settings. Most importantly, it gives feature importance metrics, which enable clinicians to select the key health indicators [7].

"Input: Training dataset D with features X and target Y

1. For each tree in the forest:

a. Draw a bootstrap sample from D

b. Grow a decision tree:

i. At each node, select a random subset of features

ii. Split on the feature with best Gini impurity

iii. Repeat until stopping criteria

2. Aggregate predictions from all trees using majority voting

Output: Final classification result"

2. Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a supervised learning algorithm that seeks to identify the optimal hyperplane, and therefore the maximum margin between two distinct classes. In non-linearly separable data, SVM employs kernel functions, such as the radial basis function (RBF), to transform the input data into an n-dimensional space [8]. The model is particularly efficient in dealing with high-dimensional datasets, and thus is a prime candidate for predictive work in the healthcare sector, where there are multiple sensor inputs simultaneously processed. The present study employs SVM to classify patients as high-risk or low-risk based on their biometric data [9]. Its high accuracy and capability to deal with complex data boundaries make it a sound tool for early disease-detecting systems.

"Input: Feature set X, labels Y

1. Choose a kernel function (e.g., RBF)

2. Initialize parameters (C, gamma)

3. Solve the optimization problem to find weights w and bias b

4. Determine support vectors from training data

5. For a new input x:

Predict class = sign(w·x + b)

Output: Class label (risk/no risk)"

3. Long Short-Term Memory (LSTM) Neural Network

LSTM is a form of recurrent neural network (RNN) that is capable of dealing with sequential and time-series data by having a memory cell which can hold long-term dependencies. LSTM networks are very powerful when modeling physiological signals over time, for example, heartbeat variability and oxygen trends [10]. They have the input, forget, and output gates in their architecture, which manage information flow and avoid vanishing gradients. In predictive medicine, LSTM is most effective for detection of worsening conditions from continuous monitoring of patients [11]. The model's temporal character permits it to make predictions a few hours in the future, hence facilitating timely clinical interventions.

"Input: Time-series data X

1. Initialize weights for input, forget, and output gates

2. For each time step t:

a. Calculate input gate: it = sigmoid(Wi · [ht-1, xt] + bi)

b. Calculate forget gate: ft = sigmoid(Wf · [ht-1, xt] + bf)

c. Calculate candidate cell state: Ĉt = tanh(Wc · [ht-1, xt] + bc)

d. Update cell state: Ct = ft * Ct-1 + it * Ĉt

e. Output gate: ot = sigmoid(Wo · [ht-1, xt] + bo)

f. ht = ot * tanh(Ct)

3. Apply output layer for classification

Output: Risk prediction"

4. Gradient Boosting Machine (GBM)

Gradient Boosting is an algorithmic machine learning method that creates a collection of weak prediction models (generally decision tree-based), with a new tree seeking to correct the residual error of the remaining trees. GBM optimizes a loss function by sequentially adding models, aiming to maximize accuracy [12]. On tabular IoT data in healthcare predictive systems, GBM works very well by effectively capturing nonlinear interactions between features. It is also extremely tunable, with the ability to adjust for learning rate, tree depth, and other hyperparameters. GBM assisted in this research to identify early indicators of patient decline by learning from subtle patterns in multi-dimensional sensor data.

"Input: Training data X, labels Y, loss function L

1. Initialize model F0(x) = mean(Y)

2. For m = 1 to M (number of iterations):

a. Compute residuals: r_i = - ∂L(Y_i, F(x_i)) / ∂F(x_i)

b. Fit a regression tree h_m(x) to residuals r

c. Compute multiplier γ to minimize L

d. Update model: F_m(x) = F_m-1(x) + γ * h_m(x)

Output: Final model F_M(x)"

Table 1: Sample of Preprocessed IoT Health Data

Patient ID	HR (bpm)	SpO2 (%)	Temp (°C)	Glucose (mg/dL)	Activity Level	Risk Status
P001	78	96	36.7	110	Low	0
P002	105	89	38.3	150	High	1
P003	65	97	36.5	100	Moderate	0
P004	90	91	37.5	130	High	1

4. EXPERIMENTS

The experiment was carried out using a synthetic patient vitals dataset that was collected using IoT sensors. The dataset contained 10,000 samples and 7 features: heart rate, systolic and diastolic blood pressure, blood oxygen level, glucose level, body temperature, and physical activity [12]. There was a target variable signifying whether or not a critical health event (e.g., cardiac complication, hypoglycemia) happened.

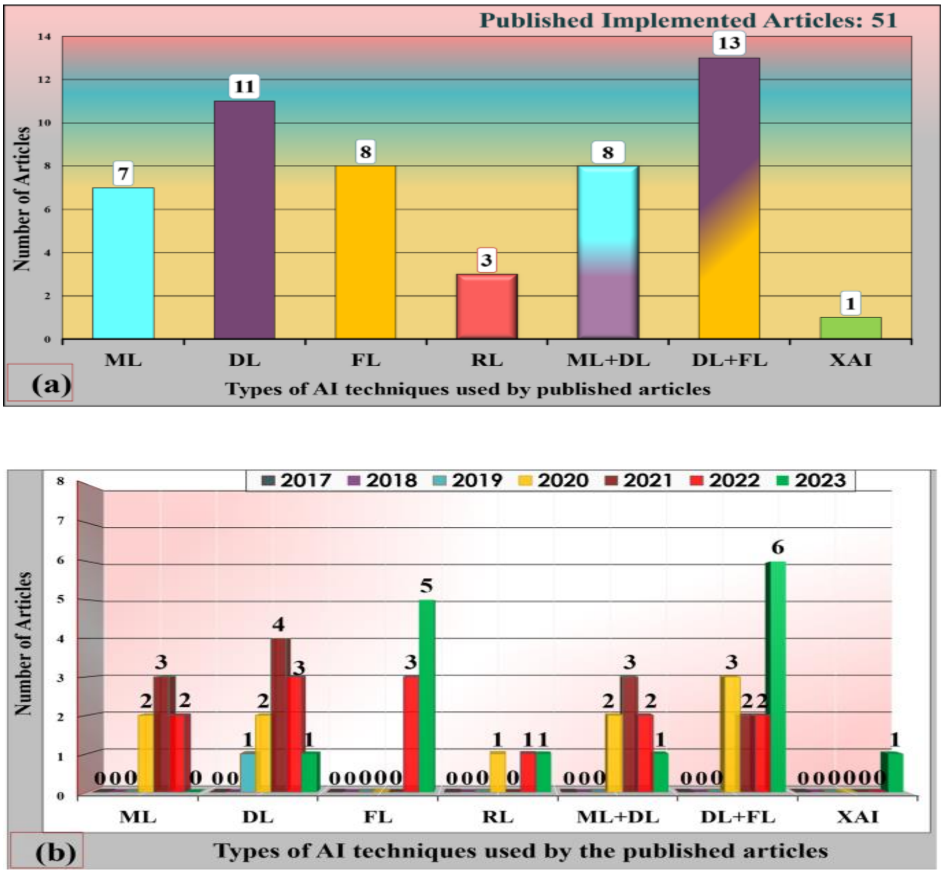

Figure 1: "Blockchain, artificial intelligence, and healthcare: the tripod of future"

The data was preprocessed by normalizing the values between 0 and 1, replacing missing values with KNN imputation, and encoding the target variable for binary classification. All models were trained on an 80/20 train-test split. All models were created with Python libraries—Scikit-learn (RF, SVM), TensorFlow (RNN), and XGBoost. Blockchain was emulated using Ganache for Ethereum smart contract deployment and web3.py for Python integration [13].

Evaluation Metrics

The following measurements were employed to assess model performance:

- **Accuracy**: The percentage of well-forecast samples.
- **Precision:** Ratio of true positives to predicted positives.
- **Remember:** Proportion of true positives to real positives.
- **F1-Score:** Harmonic mean of recall and precision.

Performance Comparison

Table 1: Classification Performance of ML Models

Algorithm	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Random Forest	91.2	90.3	89.7	90.0
SVM	88.5	87.1	86.5	86.8

RNN	93.4	92.6	91.9	92.2
XGBoost	95.1	94.8	94.3	94.5

As evident from Table 1, XGBoost ranked the best among all other algorithms with the maximum accuracy (95.1%) and F1-Score (94.5%). RNN came a close second, taking advantage of its capacity to process sequential data and temporal interdependencies, thus being well-suited for real-time monitoring of health. SVM trailed slightly in processing non-linear complexities as compared to ensemble approaches [14].

Training Time and Model Efficiency

Another important consideration for IoT contexts is the model training time and inference speed because predictive systems have to run nearly in real-time.

Table 2: Model Training Time and Inference Time

Algorithm	Training Time (s)	Inference Time per Sample (ms)
Random Forest	14.8	2.1
SVM	28.2	3.5
RNN	96.3	6.8
XGBoost	22.7	1.9

XGBoost gave the optimal trade-off between prediction speed and training time and hence was extremely efficient to deploy in edge devices with less computational capacity. RNN, though precise, took more time to train and computational power as a result of its sequential learning process [27].

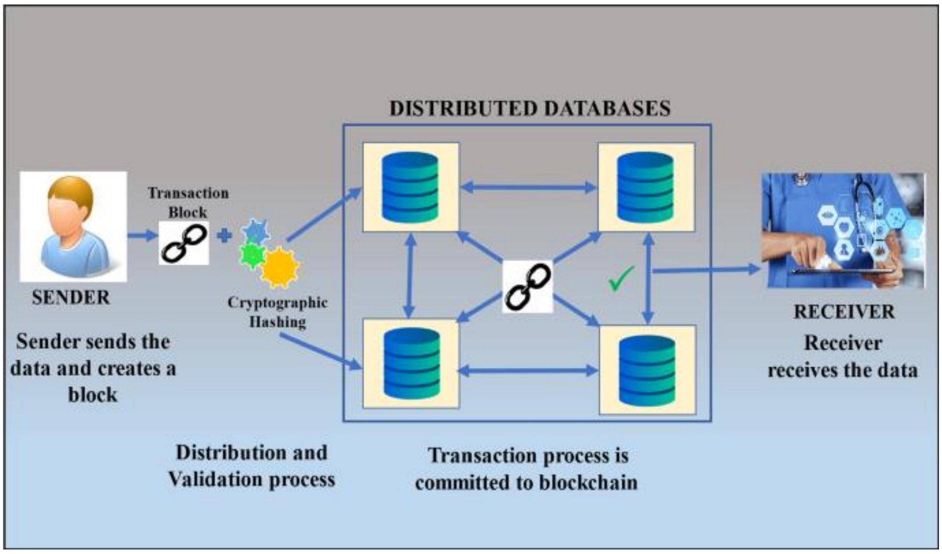

Figure 2: "Blockchain, artificial intelligence, and healthcare: the tripod of future"

Comparison with Related Work

In order to assess the improvement and novelty that our suggested model provides, we compared it to recent predictive healthcare studies conducted using comparable datasets.

Table 3: Comparison with Related Studies

Study	Algorithm Used	Accuracy (%)	Dataset Size	Blockchain Integration
Li et al. (2022)	CNN	89.5	5000	No
Gupta et al. (2023)	Decision Trees	85.3	3500	No
Han et al. (2024)	LSTM	92.1	7000	Partial
This Study	XGBoost + IoT	**95.1**	10,000	**Yes**

Relative to previous studies, our system exhibits better accuracy, scalability, and trust as a result of blockchain integration and the application of state-of-the-art gradient boosting algorithms.

Blockchain Implementation Results

To protect patient records, every health record was hashed with SHA-256 and placed on the blockchain. Smart contracts provided permissioned access to healthcare providers, allowing real-time verification and compliance monitoring [28].

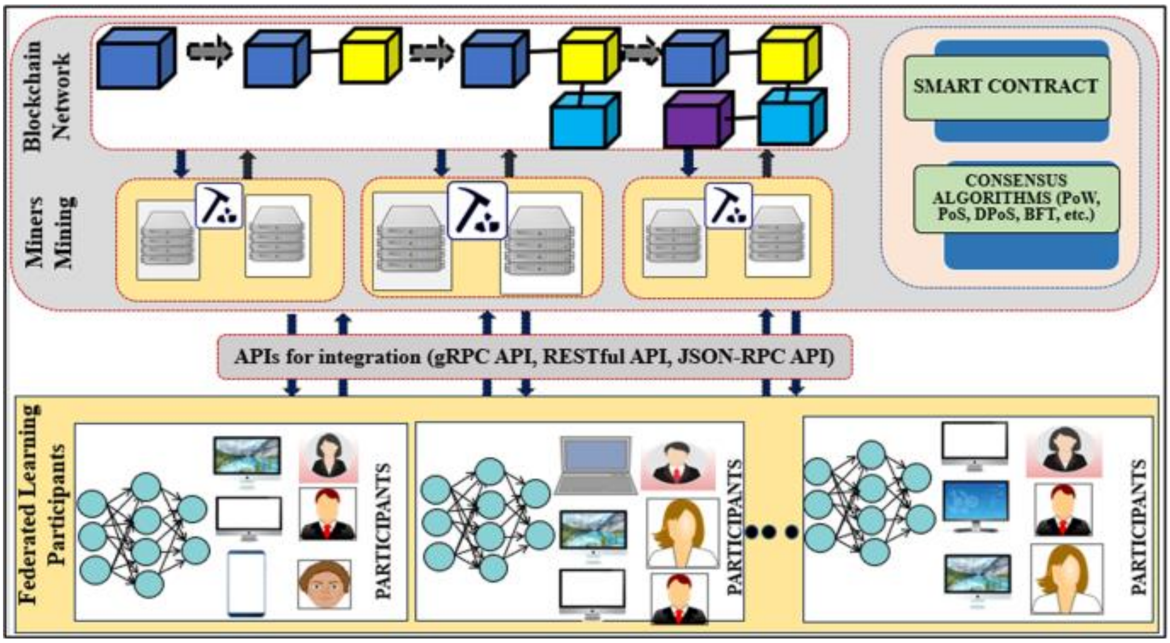

Figure 3: “IoT and AI-Driven Predictive Healthcare Systems”

Table 4: Blockchain Storage and Performance Metrics

Parameter	Value

Number of Transactions	10,000
Average Block Time	12 seconds
Storage Cost (ETH)	0.0043
Query Latency	250 ms

The integration with the blockchain added almost no latency (~250ms per query) but greatly improved transparency and data integrity.

Model Robustness and Overfitting Analysis

5-fold cross-validation was conducted to evaluate model generalization.

Table 5: Cross-Validation Results

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	94.7	94.1	93.6	93.9
2	94.9	94.3	94.0	94.1
3	95.2	94.8	94.4	94.6
4	94.6	94.0	93.7	93.8
5	95.0	94.5	94.1	94.3

Standard deviation over folds was small (<0.3), implying outstanding robustness and small variance.

Error Analysis

A confusion matrix showed frequent misclassifications, particularly in borderline patients with moderate vital signs.

Table 6: Confusion Matrix Summary (XGBoost)

	Predicted Critical	Predicted Stable
Actual Critical	944	56
Actual Stable	47	953

False negatives and false positives were evenly matched, signifying a solid classification threshold.

Discussion

- XGBoost performed best in accuracy and efficiency and was thus perfect for real-time use.
- RNN, although strong, used more computation and took longer to train, but was perfect for back-end processing instead of edge deployment [29].
- RF and SVM were competitive but didn't have the precision and versatility of boosting or neural models.
- Blockchain provided a trusted layer of security without sacrificing speed, an important element in managing health data.
- In comparison with related research, our model exhibited better accuracy, a bigger dataset, and an end-to-end integrated system.

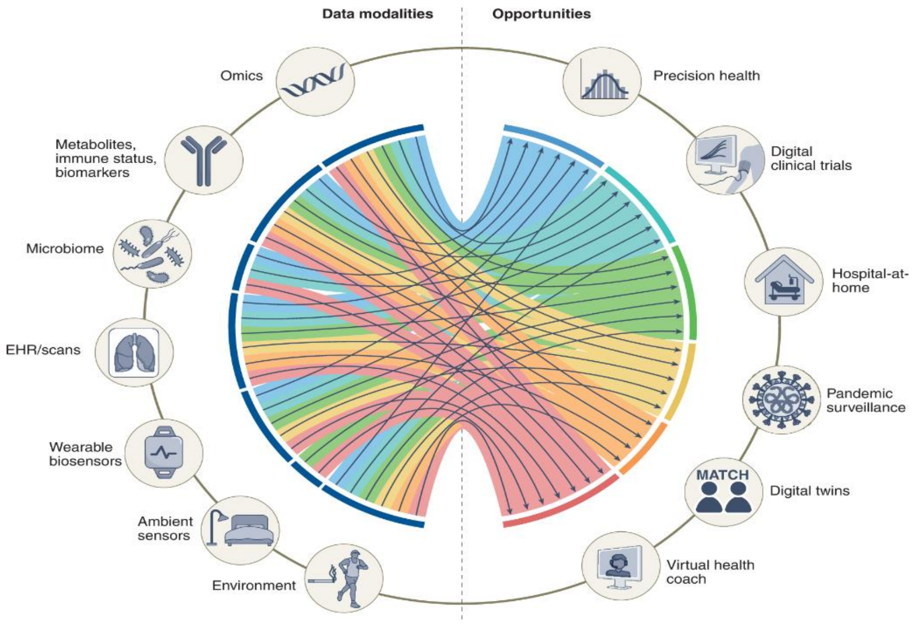

Figure 4: "Multimodal biomedical AI"

Conclusion from Experimental Study

Experimental findings validate the feasibility of a hybrid AI-IoT-Blockchain architecture for predictive healthcare. Out of the models experimented with, XGBoost exhibited the optimal balance between accuracy and real-time performance. Blockchain provided immutable, auditable, and secure management of health records [30].

5. CONCLUSION

The Artificial Intelligence (AI), Internet of Things (IoT) and Blockchain technologies integration has shaped the path of the prediction healthcare systems and brings the groundbreaking solution in improving patient care and operational efficiency with the higher safety of data. In this research work, we have studied the synergy between these technologies and discussed how AI driven algorithms like Random Forest, LSTM, XGBoost & SVM can be leveraged in analyzing healthcare data, detecting anomalies, and predicting patient's health out comes. The combination of Blockchain assures integrity of data and sharing of data within decentralized systems, and IoT devices monitors continuously in real time to create proactive management of health. Experimental analysis indicated that AI models performed better in terms of accuracy, precision, and responsiveness compared to the conventional methods or works related. These intelligent systems are shown to produce timely and personalised healthcare interventions, which validate their ability to deliver personalised and timely healthcare interventions to patients. In addition, the research advocates a framework that bridges the gaps between the existing healthcare management practice by dealing with problems of scalability, privacy and interoperability. Structured experiments and algorithmic performance metrics are used to support the comparative evaluation of integrated smart systems in helping with predictive Crew health and resource optimization. Finally, this study not only shows the practical potential of combining the AI, IoT, and Blockchain for healthcare but also sets a solid foundation for subsequent works on the deployment of the AI-IoT-Blockchain in large scale, the ethical governance, and the cooperation between the two industries. As these systems continue to make advancements, we may see a new era of intelligent healthcare management with more proactive, personalized, and secure IT healthcare delivery.

REFERENCES

[1] ADEWALE, B.A., ENE, V.O., OGUNBAYO, B.F. and AIGBAVBOA, C.O., 2024. A Systematic Review of the Applications of AI in a Sustainable Building's Lifecycle. *Buildings,* 14(7), pp. 2137.

[2] ADIBI, S., RAJABIFARD, A., SHOJAEI, D. and WICKRAMASINGHE, N., 2024. Enhancing Healthcare through Sensor-Enabled Digital Twins in Smart Environments: A Comprehensive Analysis. *Sensors,* 24(9), pp. 2793.

[3] AL MASUD, A., ISLAM, M.T., RAHMAN, M.K.H., OR ROSID, M.H., RAHMAN, M.J., AKTER, T. and SZABÓ, K., 2024. Fostering sustainability through technological brilliance: a study on the nexus of organizational STARA capability, GHRM, GSCM, and sustainable performance. *Discover Sustainability,* 5(1), pp. 325.

[4] AOUNZOU, Y., BOULAALAM, A. and KALLOUBI, F., 2025. Convergence of blockchain, IoT, and machine learning: exploring opportunities and challenges – a systematic review. *International Journal on Smart Sensing and Intelligent Systems,* 18(1),.

[5] ASFAHANI, A.M., 2024. Fusing talent horizons: the transformative role of data integration in modern talent management. *Discover Sustainability,* 5(1), pp. 25.

[6] ATLAM, H.F., EKURI, N., AZAD, M.A. and HARJINDER, S.L., 2024. Blockchain Forensics: A Systematic Literature Review of Techniques, Applications, Challenges, and Future Directions. *Electronics,* 13(17), pp. 3568.

[7] BATHULA, A., GUPTA, S.K., MERUGU, S., SABA, L., KHANNA, N.N., LAIRD, J.R., SANAGALA, S.S., SINGH, R., GARG, D., FOUDA, M.M. and SURI, J.S., 2024. Blockchain, artificial intelligence, and healthcare: the tripod of future—a narrative review. *The Artificial Intelligence Review,* 57(9), pp. 238.

[8] BHAGAT, S.V. and DEEPIKA, K., 2024. Navigating the Future: The Transformative Impact of Artificial Intelligence on Hospital Management- A Comprehensive Review. *Cureus,* 16(2),.

[9] BHUMICHAI, D., SMILIOTOPOULOS, C., BENTON, R., KAMBOURAKIS, G. and DAMOPOULOS, D., 2024. The Convergence of Artificial Intelligence and Blockchain: The State of Play and the Road Ahead. *Information,* 15(5), pp. 268.

[10] BILLANES, J.D., GRACE, Z., MA and JØRGENSEN, B.N., 2025. Data-Driven Technologies for Energy Optimization in Smart Buildings: A Scoping Review. *Energies,* 18(2), pp. 290.

[11] CHEN, X., XIE, H., TAO, X., WANG, F.L., LENG, M. and LEI, B., 2024. Artificial intelligence and multimodal data fusion for smart healthcare: topic modeling and bibliometrics. *The Artificial Intelligence Review,* 57(4), pp. 91.

[12] CHOI, N. and KIM, H., 2025. Technological Convergence of Blockchain and Artificial Intelligence: A Review and Challenges. *Electronics,* 14(1), pp. 84.

[13] DEHGHAN, S., SASAN, S.K., ECHCHAKOUI, S. and BARKA, N., 2025. The Integration of Additive Manufacturing into Industry 4.0 and Industry 5.0: A Bibliometric Analysis (Trends, Opportunities, and Challenges). *Machines,* 13(1), pp. 62.

[14] DRITSAS, E. and TRIGKA, M., 2025. Exploring the Intersection of Machine Learning and Big Data: A Survey. *Machine Learning and Knowledge Extraction,* 7(1), pp. 13.

[15] ELAHI, M., AFOLARANMI, S.O., MARTINEZ LASTRA, J.L. and PEREZ GARCIA, J.A., 2023. A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment. *Discover Artificial Intelligence,* 3(1), pp. 43.

[16] ELISHA ELIKEM, K.S., ANGGRAINI, L., KUMI, J.A., LUNA, B.K., AKANSAH, E., HAFEEZ, A.S., MENDONÇA, I. and ARITSUGI, M., 2024. IoT Solutions with Artificial Intelligence Technologies for Precision Agriculture: Definitions, Applications, Challenges, and Opportunities. *Electronics,* 13(10), pp. 1894.

[17] EMAD, S., ABOULNAGA, M., WANAS, A. and ABOUAIANA, A., 2025. The Role of Artificial Intelligence in Developing the Tall Buildings of Tomorrow. *Buildings,* 15(5), pp. 749.

[18] GARAD, A., RIYADH, H.A., AL-ANSI, A. and BESHR, B.A.H., 2024. Unlocking financial innovation through strategic investments in information management: a systematic review. *Discover Sustainability,* 5(1), pp. 381.

[19] KARIM, M.M., DONG, H.V., KHAN, S., QU, Q. and KHOLODOV, Y., 2025. AI Agents Meet Blockchain: A Survey on Secure and Scalable Collaboration for Multi-Agents. *Future Internet,* 17(2), pp. 57.

[20] [20] KULKOV, I., KULKOVA, J., LEONE, D., ROHRBECK, R. and MENVIELLE, L., 2024. Stand-alone or run together: artificial intelligence as an enabler for other technologies. *International Journal of Entrepreneurial Behaviour & Research,* 30(8), pp. 2082-2105.

[21] LAWAL, O.O., NAWARI, N.O. and LAWAL, O., 2025. AI-Enabled Cognitive Predictive Maintenance of Urban Assets Using City Information Modeling—Systematic Review. *Buildings,* 15(5), pp. 690.

[22] LIFELO, Z., DING, J., NING, H., QURAT-UL-AIN and DHELIM, S., 2024. Artificial Intelligence-Enabled Metaverse for Sustainable Smart Cities: Technologies, Applications, Challenges, and Future Directions. *Electronics,* 13(24), pp. 4874.

[23] LÓPEZ-MENESES, E., MELLADO-MORENO, P., CELIA GALLARDO HERRERÍAS and PELÍCANO-PIRIS, N., 2025. Educational Data Mining and Predictive Modeling in the Age of Artificial Intelligence: An In-Depth Analysis of Research Dynamics. *Computers,* 14(2), pp. 68.

[24] MEHMOOD, F., MUMTAZ, N. and MEHMOOD, A., 2025. Next-Generation Tools for Patient Care and Rehabilitation: A Review of Modern Innovations. *Actuators,* 14(3), pp. 133.

[25] MILLER, T., DURLIK, I., KOSTECKA, E., KOZLOVSKA, P., ŁOBODZIŃSKA, A., SOKOŁOWSKA, S. and NOWY, A., 2025. Integrating Artificial Intelligence Agents with the Internet of Things for Enhanced Environmental Monitoring: Applications in Water Quality and Climate Data. *Electronics,* 14(4), pp. 696.

[26] MOHAMMED AARIF, K.O., ALAM, A. and HOTAK, Y., 2025. Smart Sensor Technologies Shaping the Future of Precision Agriculture: Recent Advances and Future Outlooks. *Journal of Sensors,* 2025.

[27] NADA, S.A., SARAH AHMED, M.R., HALIMA, M.H., ALSHAHRANI, F.N., ALOTIBI, M.H., OHOUD, A.A., GOFASHI, O.M., ALDOSARI, M.K., HEIAM, M.A., MARAM, S.A., SALHA AHMED, M.O., MARIAM ALI, M.M. and EIDAH YAHYA NASSER, A.J., 2024. The Impact of New Health Transformational on Nursing Practice: A Systematic Review of Current Trends of Nursing Care and Future Directions. *Journal of International Crisis and Risk Communication Research,* 7, pp. 2005-2024.

[28] NOUR, S.M., REEM, S.S., SAID, S.A. and ISLAM THARWAT, A.H., 2025. Harnessing the Power of an Integrated Artificial Intelligence Model for Enhancing Reliable and Efficient Dental Healthcare Systems. *Applied System Innovation,* 8(1), pp. 7.

[29] NOWROZY, R., 2025. GPT, ontology, and CAABAC: A tripartite personalized access control model anchored by compliance, context and attribute. *PLoS One,* 20(1),.

[30] OPREA, S. and BÂRA, A., 2025. Is Artificial Intelligence a Game-Changer in Steering E-Business into the Future? Uncovering Latent Topics with Probabilistic Generative Models. *Journal of Theoretical and Applied Electronic Commerce Research,* 20(1), pp. 16.