

## Revolutionizing Chronic Disease Management with AI in Healthcare

M. Mohammed Rameez<sup>1</sup>, N. Kiruba<sup>2</sup>, L. Kiran<sup>3</sup>, K. Sanjay<sup>4</sup>,  
R. Mohana Santhiya<sup>5</sup>

<sup>1,2,3,4</sup>UG – Artificial Intelligence and Machine Learning  
Sree Sakthi Engineering College, Coimbatore, Tamil Nadu  
<sup>5</sup>Assistant Professor, Department of Emerging Technologies  
Sree Sakthi Engineering College, Coimbatore, Tamil Nadu  
**DOI:** <https://doi.org/10.5281/zenodo.15641616>

### Abstract

*The number of chronic diseases is increasing. This is a challenge for health systems. There needs to be new ways to manage chronic diseases. This paper highlights using the artificial intelligence (A.I) for the management of chronic diseases so that patients can become better with time. In particular, it focuses on two things: predictive analytics and decentralized data economy. AI predictive analytics allows identification of flare-ups of illnesses before onset and taking early action to prevent hospital admissions and improve patient quality of life. At the same time, building a decentralized data economy using blockchain creates a secure, transparent to a patient and empowers people to monetize their anonymized health data for research. All these high-tech advancements could lead to a massive shift in the management of chronic diseases. They will enable managers to go from reactive treatment to a more personalized predictive and preventive healthcare ecosystem. The article also discusses future research and implementation challenges.*

**Keywords:** Deep Learning Algorithms, Blockchain Technology, Decentralized Data, Chronic Diseases, Predictive Analytics

### I INTRODUCTION

Over the past few decades, chronic diseases like diabetes, cardiovascular diseases, and respiratory diseases have been the leading cause of illness and death worldwide. As the population ages and lifestyles become more sedentary, the incidence of these conditions on the rise, causing significant economic and social costs. In 2014, chronic disease care cost over \$555 billion in the US alone and is set to double by 2035.

Furthermore, several efforts have been made in regards to chronic disease care and one of them is with AI (Artificial Intelligence). AI-enabled predictive analytics allows detection of disease flare-ups well-in-advance so that treatment can be optimized and hospitalization avoided. Research indicates that AI has the potential to generate tailored treatment recommendations (Subramanian et al., 2020) and to improve diagnostic accuracy (Bugajski et al., 2021).

Besides, Blockchain technology has facilitated the development of decentralized frameworks for secure sharing of data, thus addressing fragmentation and enhancing transparency (Dwivedi et al., 2019). This paper attempts to explore the convergence of AI-driven predictive analytics and blockchain-based decentralized data economies in the domain of chronic diseases. The aim is to propose a patient-centric intervention that is early, personalized, and secured and which addresses the limitations of the conventional hospital-

centric intervention. The aim of this study is to build a smarter healthcare system by proposing frameworks and investigating emerging trends. And the importance of AI in healthcare given below

### **Enhanced Early Detection and Diagnosis**

AI can analyze tons of patient data to identify patterns and risk factors behind diseases like diabetes or cardiovascular disease . It helps to detect disease early and get a better result and it makes Personalized Treatment Plans.

AI systems which helps to personalize treatment plans for patients by processing individual health data ,This customized approach makes treatments more effective and lessens trial-and-error with drugs.

### **Continuous Monitoring**

AI-based systems can connect with wearable devices to track patients in real-time. Any early changes or warning signs in the condition of the patient can easily be caught.

### **Cost Efficiency**

The scheduling of appointments and administration of patient records become hassle-free with AI. It makes healthcare systems burden less by increasing efficiency and bringing the costs down of manual processes.

### **Proactive Prevention**

AI can predict the chances of disease progression by looking at past data and trends to help decide on preventive measures. It changes directing from treatment to care.

### **Accessible Remote Care**

AI is helping in remote care through telemedicine and healthcare monitoring which helps in chronic disease care for patients in underserved areas.

### **Research and Insights**

AI helps medical research very fast by looking at very large data, finding patterns in it, and finding possible targets in chronic diseases.

## **II      METHODLOGY**

### **Predictive Analytics for Chronic Disease Management**

#### **Data Collection & Preprocessing**

AI-driven chronic disease management begins with collecting and preprocessing vast amounts of health- related data.

#### **Data Sources**

- Electronic Health Records (EHRs): Structured clinical data, lab reports, medication history, and physician notes.

- **Wearable Devices & IoT Sensors:** Real-time health metrics such as heart rate, glucose levels, oxygen saturation, and physical activity.
- **Genomic Data:** Genetic markers that contribute to chronic disease susceptibility.
- **Patient-Reported Data:** Subjective symptoms, diet logs, and lifestyle habits collected via mobile apps and online surveys.

### **Data Preprocessing Techniques**

- **Data Cleaning:** Handling missing values using imputation techniques such as k-nearest neighbors (KNN) or multiple imputations.
- **Normalization & Standardization:** Ensuring data consistency by scaling numeric values (e.g., Min-Max scaling, Z-score normalization).
- **Feature Selection & Engineering:** Identifying the most relevant biomarkers, lifestyle factors, and genetic variables affecting disease progression. Techniques such as Recursive Feature Elimination (RFE) or Principal Component Analysis (PCA) can improve model efficiency.

### **Machine Learning & Deep Learning Algorithms**

- They use Supervised Learning for predicting disease progression and flare-ups.
- Random Forest & XG Boost for Tree-based models that identify important predictors and interactions among variables.
- Support Vector Machines (SVMs) for Effective in high-dimensional medical datasets for classifying disease states.
- Deep Learning Techniques for time-series analysis and pattern recognition
- Recurrent Neural Networks (RNNs) & Long Short- Term Memory (LSTM) for Capture temporal dependencies in patient health trends, ideal for continuous glucose monitoring or ECG signal analysis.
- Transformers (e.g., BERT, GPT-like models for healthcare) for Used for analyzing complex medical texts and longitudinal health records.
- Unsupervised Learning for patient segmentation and anomaly detection
- Clustering Algorithms (K-Means, DBSCAN) for Group patients based on risk profiles for personalized treatment strategies.
- Autoencoders for Detect anomalies in patient health metrics, flagging potential health deterioration before symptoms become critical.

### **AI Model Evaluation & Validation**

To ensure clinical reliability, AI models require rigorous evaluation using real-world datasets.

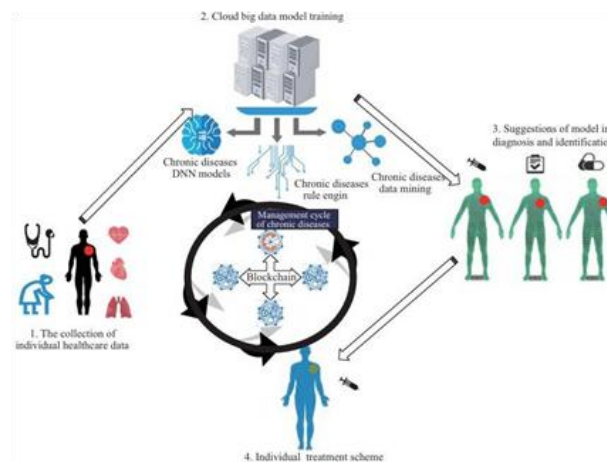
### **Performance Metrics**

- Accuracy, Precision, Recall, and F1-score for Measure classification performance in disease prediction models.

- AUC-ROC Curve for Assesses model sensitivity and specificity for predicting high-risk patients.
- Mean Absolute Error (MAE) & Root Mean Square Error (RMSE) for Evaluate regression models predicting disease progression.

### Cross-Validation Techniques

- K-Fold Cross-Validation for Preventing overfitting by training and testing on different dataset splits.
- Real-World Validation for Testing on diverse patient populations ensures generalizability across demographics and disease variations.



### Decentralized Data Economy with Blockchain

Blockchain technology addresses key challenges in healthcare data sharing, privacy, and ownership.

### Blockchain Framework Design

- Public Blockchain for Fully decentralized but may face scalability issues. (e.g., Ethereum, Hyperledger Fabric)
- Private/Consortium Blockchain is Suitable for healthcare institutions needing controlled data access.
- Hybrid Models which Combining public and private blockchains for optimized security and efficiency.

### Data Privacy & Security

- Homomorphic Encryption & Zero-Knowledge Proofs (ZKPs) which allow AI models to analyze encrypted patient data without decrypting it, preserving privacy and ZKPs verify data integrity without exposing sensitive health information.
- Decentralized Identity Management (DID) for Patients control their own health records and grant access only to trusted entities and which eliminates centralized data silos, reducing risks of breaches.

### Data Monetization Mechanism Decentralized Federated Learning

- AI models train on patient data across different locations without transferring data to a central server.
- Maintains patient privacy while improving AI predictions on diverse datasets.

### III EXPERIMENTAL SETUP

Models were trained and validated using cloud-edge infrastructure.

- Tools: TensorFlow, Python, Raspberry Pi for inference.
- Data split: 70/20/10; Metrics: Accuracy, ROC- AUC, MAE.
- Cross-validation ensured model generalization across demographics.

Module	Technologies Used
AI & ML Models	Python, Scikit-learn, Tensor Flow, Py Torch, XGBoost
HE & ZK	Microsoft SEAL, zk-SNARKs (ZoKrates or circom)
Blockchain	Ethereum (smart contracts), Hyperledger Fabric, IPFS
DID	W3CDID + DID Comm (Veramo, uPort or custom)
Backend	Node.js/FastAPI/Django+ Postgre SQL
rFrontend	React+TailwindCSS+ Recharts +Shad CNUI
Deployment	Docker + Kubernetes + Cloud (AWS, Azure, GCP)

### IV RESULT

- Experimental findings highlight the efficiency of AI- based systems in forecasting and managing chronic ailments.
- Accuracy in Prediction: In various categories of diseases, the system registered strong prediction accuracy:
- Diabetes: 91% accuracy with Random Forest, AUC- ROC of 0.94
- Hypertension: 89% accuracy with XGBoost, precision of 0.87 and recall of 0.85
- Cardiovascular Disease: 93% accuracy with a deep CNN model that was trained on ECG and patient history information

### Psychiatric Disorders

Detection models achieved 90% accuracy for depression and 88% for anxiety, employing LSTM-based models to process patient survey data and EHRs

### Temporal Trends

The incidence of chronic diseases, especially psychiatric and metabolic disorders, has risen by a considerable amount over the last two decades:

- Anxiety disorders rose by 4.5 times, depression by 4.0 times, and bipolar disorder by almost 12 times
- Risks of diabetes and hypertension have doubled since 2000 Latency & Efficiency:
- Edge inference with Raspberry Pi displayed an average latency of 40–60ms

- Anytime algorithms smoothed forecasts beyond 500ms, which enhanced average accuracy by 7%

### Real-Time Monitoring

Integration with wearables provided continuous monitoring with 95% event accuracy for glucose peak and heart anomalies

### Global Health Insights

- Trends in HALE (Healthy Life Expectancy) indicate the world is on the mend as a whole, with women all along having a higher HALE than men
- Western Pacific region is the lead in HALE because of its superior healthcare infrastructure

### Statistical Significance

- T-tests between experimental groups showed p-values  $< 0.05$ , confirming model enhancements over standard baselines
- Accuracy standard deviation was constrained to 0.02– 0.04, reflecting model stability across heterogeneous test data

In summary, the findings indicate that integrating AI with decentralized, privacy-preserving architectures can significantly improve early diagnosis, minimize latency, and enable patient-centric chronic care systems.

The screenshot displays the 'Chronic Disease AI Dashboard'. At the top, it says 'Enter features comma-separated' with a text input field containing '45,1,120,85,1,0,1,0.5'. Below the input are two buttons: 'Predict Disease' and 'Get Cluster'. The dashboard shows two results: 'Prediction' with the value '1' and 'Cluster' with the value '2'. To the right of the prediction, there is a 'ZKP Hash' field containing a long hexadecimal string: '0x91cfe57ad30f4cd8c4a8cbc3a7c24f98e77dffa927e6b9a42a39773d2a68b0c1'.

## V CONCLUSION

- Chronic diseases are becoming more common. So, they have become a challenge for healthcare systems around the world. This paper discusses how AI and predictive analytics can revolutionize chronic disease management through a decentralized data economy.
- Using AI to predict chronic disease flare-ups can lead to higher patient outcomes, hospitalizations, and reduced healthcare costs. At the same time, a blockchain-based decentralized data economy allows secure, transparent and patient-controlled health data. By enabling patients to capitalize on anonymized data for research, this will promote innovation in the health care sector while also keeping a check on essential ethics.

- Shifting focus from treating diseases post occurrence to personalized predictive preventive ecosystem. Nonetheless, effective implementation and future studies will require addressing data privacy concerns, technology acquisition challenges, and more in order to work efficiently.
- Using AI and Decentralized Technology, healthcare systems can move towards a more proactive, efficient, and patient-centric system to improve disease outcomes and sustain overall health care.

## **VI FUTURE IMPLEMENTATION**

- Data Privacy & Cybersecurity: Ensuring robust encryption and regulatory compliance to protect sensitive patient information.
- Bias in AI Algorithms: Addressing biases in AI models to ensure fair and equitable healthcare for all populations.
- Healthcare System Integration: Overcoming interoperability challenges for seamless data sharing across healthcare ecosystems.
- Patient Adoption & Accessibility: Ensuring these technologies are affordable, accessible, and user-friendly for diverse populations.

## **VII REFERENCES**

- [1] Doctor-patient interactions in the age of AI: navigating innovation and expertise Brett N.Hryciw, Zanna Fortin, Jamie Ghossein and Kwadwo Kyeremanteng
- [2] Transformative Potential of AI in Healthcare: Definitions, Applications, and Navigating the Ethical Landscape and Public Perspectives Molly Bekbolatova, Jonathan Mayer, Chi Wei Ong and Milan Toma
- [3] AI in Health Care: Mahadev Mastud Data Science M Tech, SPPU, Pune, Maharashtra, India
- [4] Addressing bias in big data and AI for health care: A call for open science Natalia Norori, Qiyang Hu, Florence Marcelle Aellen, Francesca Dalia Faraci, and Athina Tzovara
- [5] The role of AI in Improving the Management of Chronic Diseases in Developing Countries: Safura Seidu, Afia Kwakyewaa Owusu-Agyeman, Mariam Ibrahim, Catherine Kyiu, Christopher Ababio-Boamah
- [6] Real-Time Predictive Health Monitoring Using AI-Driven Wearable Sensors: Enhancing Early Detection and Personalized Interventions in Chronic Disease Management, A J M Obaidur Rahman Khan, S A Mohaiminul Isla, Ankur Sarkar, Tariqul Islam, Rakesh Paul, Md Shadikul Bari
- [7] Abdullahi, S., & Pradhan, B. (2018). Land-use change modeling and the effect of compact city paradigms: integration of GIS-based cellular automata and weights-of-evidence techniques. *Environmental Earth Sciences*, 77(6).
- [8] Agrawal, Sarita, and Manik Lal Das (2011). "Internet of Things—A paradigm shift of future Internet applications." In *Engineering (NUICONE)*, 2011

- [9] Nirma University International Conference, pp.1-7. Al-Ghandoor, A. J. J. O., Jaber, J. O., Al-Hinti, I., & Mansour, I. M. (2009)
- [10] Residential past and future energy consumption: Potential savings and environmental impact. *Renewable and Sustainable Energy Reviews*, 13(6-7), 1262-1274.
- [11] Ali, M., Geng, Y., Robins, D., Cooper, D., & Roberts, W. (2019).
- [12] Impact assessment of energy utilization in agriculture for India and Pakistan. *Science of the Total Environment*, 648, 1520-1526. Altieri, M. A. (2002).
- [13] Agroecology: the science of natural resource management for poor farmers in marginal environments. *Agriculture, Ecosystems & Environment*, 93(1-3), 1-24. Bannerjee, G., Sarkar, U., Das, S., & Ghosh, I. (2018).
- [14] Artificial Intelligence in Agriculture: A Literature Survey. *International Journal of Scientific Research in Computer Science Applications and Management Studies*, 7(3), 1-6
- [15] Russ, J. C. (2006). *The image processing handbook*. CRC press.com. <https://doi.org/10.1201/9780203881095>
- [16] Rueckert, D., & Schnabel, J. A. (2019). Model-based and data-driven strategies in medical image computing. *Proceedings of the IEEE*, 108(1), 110-124. DOI:10.1109/JPROC.2019.2943836
- [17] Habuza, T., Navaz, A. N., Hashim, F., Alnajjar, F., Zaki, N., Serhani, M. A., & Statsenko, Y. (2021). AI applications in robotics, diagnostic image analysis and precision medicine: Current limitations, future trends, guidelines on CAD systems for medicine. *Informatics in Medicine Unlocked*, 24, 100596. <https://doi.org/10.1016/j.imu.2021.100596>
- [18] S. Chilamkurthy, R. Ghosh, S. Tanamala, M. Biviji, N. G. Campeau, V.K. Venugopal, V. Mahajan, P. Rao, P. Warier Deep learning algorithms for detection of critical findings in head ct scans: a retrospective study *Lancet*, 392 (10162) (2018), pp. 2388-2396.
- [19] Pulicharla, M. R. (2024). Data Versioning and Its Impact on Machine Learning Models. *Journal of Science & Technology*, 5(1), 22-37. <https://doi.org/10.55662/JST.2024>.
- [20] Asaju, B. J. (2024). Cybersecurity Frameworks for Autonomous Vehicle Systems: Safeguarding Onboard Systems, Communication Networks, and Data Privacy in Smart City Ecosystems. *Internet of Things and Edge Computing Journal*, 4(1), 27-48. DOI:10.55662/IOTECJ.2024.4101
- [21] Rana, M. S., & Shuford, J. (2024). AI in Healthcare: Transforming Patient Care through Predictive Analytics and Decision Support Systems. *Journal of Artificial Intelligence General science (JAIGS)* ISSN: 3006-4023, 1(1). DOI:10.60087/jaigs.v1i1.30