Heart Disease Prediction using Explainable A I (XAI)

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***Abstract*—**This paper surveys key application domains of Heart disease remains one of the leading causes of mortality worldwide, posing a significant challenge to healthcare systems due to its complex etiology and the need for early and accurate diagnosis. With the rapid growth of medical data and advances in computational intelligence, machine learning and deep learning models have been widely adopted for heart disease classification.

***Index Terms*—XAI-based framework,SHAP,xNoise,precision ,CNN,RNN,GRU,LSTM,SDCNN**

I. Introduction

Heart disease classification has become a critical research area due to the increasing prevalence of cardiovascular disorders and the growing demand for intelligent diagnostic systems. Traditional diagnostic methods rely heavily on physician expertise, clinical tests, and manual interpretation of patient data, which can be time-consuming and prone to subjective bias. In recent years, Artificial Intelligence has demonstrated remarkable performance in medical diagnosis by learning complex patterns from large datasets. Machine learning models such as decision trees, support vector machines, and neural networks have been successfully applied to predict heart disease with high accuracy. Despite these advances, the opacity of many AI models poses a serious challenge in healthcare, where understanding the rationale behind a prediction is as important as the prediction itself. Explainable Artificial Intelligence has emerged as a solution to this problem by making AI decisions transparent and interpretable. In heart disease classification, XAI enables clinicians to examine which clinical features influence predictions and how different risk factors interact. This interpretability is crucial for validating model outputs, ensuring patient safety, and complying with medical regulations. The integration of XAI into heart disease classification systems bridges the gap between advanced computational models and practical clinical adoption. This research focuses on developing an explainable AI methodology that not only predicts heart disease accurately but also provides meaningful explanations aligned with medical knowledge[1],[2],[3]. The proposed approach aims to improve diagnostic confidence, support clinical decision-making, and enhance patient trust by offering transparent and accountable AI outcomes. Ultimately, this study contributes to the development of ethical, reliable, and clinically applicable AI systems in cardiovascular healthcare.

Despite significant advancements in AI-based heart disease classification, the lack of interpretability in existing models remains a major obstacle to their widespread adoption in clinical practice. Most high-accuracy models function as black boxes, offering little to no explanation for their predictions. This creates uncertainty among healthcare professionals who must rely on transparent reasoning to make life-critical decisions. Without explanations, clinicians cannot verify whether a model's decision aligns with established medical principles or whether it is influenced by biased or irrelevant features. Additionally, patients are increasingly demanding clarity and accountability in AI-assisted diagnoses, especially when treatment decisions and long-term health outcomes are involved. Regulatory bodies also require AI systems used in healthcare to be explainable, fair, and auditable[4],[5],[6]. The problem, therefore, lies in designing a heart disease classification system that achieves high predictive performance while remaining interpretable and trustworthy. There is a pressing need for methodologies that can explain predictions at both global and individual patient levels. by proposing an XAI-based framework tailored specifically for heart disease classification[7],[8],[9].

1.3 Scope of Research

The scope of this research encompasses the design, implementation, and evaluation of an explainable artificial intelligence methodology for heart disease classification using structured clinical datasets. The study focuses on commonly used heart disease attributes such as age, sex, chest pain type, resting blood pressure, cholesterol levels, fasting blood sugar, electrocardiographic results, and exercise-induced indicators. The research emphasizes interpretability by integrating XAI techniques that provide both global model explanations and local, patient-specific insights. The scope includes data preprocessing, feature selection, model training, and explanation generation. While the study aims to achieve competitive classification accuracy, equal importance is given to transparency, clinical relevance, and usability by healthcare professionals. The research does not focus on real-time deployment or hardware-level optimization but instead concentrates on methodological robustness and explainability. The outcomes are intended to support clinical decision-making, medical education, and future integration into intelligent healthcare systems[10],[11],[12].

1.4.1 Disadvantages of Existing System

The primary disadvantage of existing heart disease classification systems is their lack of explainability. Black-box models fail to justify their predictions, making it difficult for clinicians to trust and adopt them in critical diagnostic scenarios. This opacity increases the risk of undetected biases, where models may rely on spurious correlations rather than medically relevant features. Existing systems also struggle with regulatory compliance, as many healthcare standards require transparent and auditable decision processes. Furthermore, the absence of interpretable outputs limits patient engagement, as individuals cannot understand why they are classified as high-risk or low-risk. Another significant drawback is the reduced ability to support clinical learning and validation, since unexplained predictions cannot be easily compared with expert knowledge. These limitations collectively hinder the integration of AI systems into routine cardiovascular care[16],[17],[18].

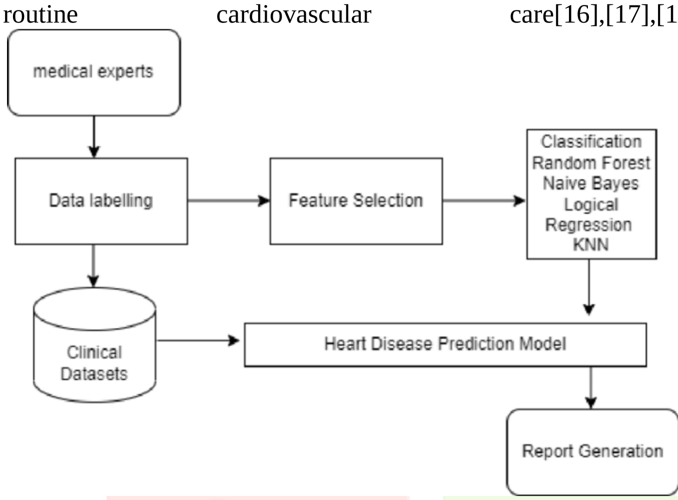

Fig.1.Structureofthesetofblocksorganizedinachain.

1.5 Proposed System

The proposed system introduces an Explainable Artificial Intelligence methodology specifically designed for heart disease classification. The system integrates interpretable machine learning models with advanced XAI techniques to ensure transparency at every stage of the decision-making process. Clinical data is preprocessed to handle missing values, normalize attributes, and enhance data quality. Feature selection methods are applied to identify medically significant risk factors, ensuring that the model focuses on relevant inputs. The classification model is designed to balance accuracy and interpretability, enabling clear reasoning behind predictions. XAI mechanisms such as feature importance analysis and local explanation models are embedded into the system to provide insights into both overall model behavior and individual patient predictions. This approach ensures that clinicians can understand which factors contribute most to heart disease risk and how changes in patient data influence outcomes. The proposed system aims to serve as a reliable decision-support tool rather than a replacement for medical professionals[19],[20].

NXT,andEthereum.Inaprivateblockchain,onlyuserswith permissions can join the network, write or send transactions to the blockchain. A company or a group of companies is usually responsible for giving users such permissions before joining the network. Examples of private blockchains are Everledger, Ripple, and Eris [13].

A. Consensus

Multiple alternative consensus mechanisms have been developedandusedinblockchaintechnology.Theseconsensus are presented and summarized in table I.

- *Proof-of-Work (PoW)*: the miners, i.e. unique nodesthat can add transactions to the chain, are financially rewardediftheyperformverification.Thus,thePoW is a costly process as the miners compete with each othertosolveamathematicalproblem.Asthenumberof miners involved increases, so does the energy cost, and processingtime[14].Asthecomplexityincreasesinthe mining process, the power consumption also increases.
- *Proof-of-Stake (PoS)*: specifically, it adopts a forging process rather than the mining process to validate transaction blocks. Here, the miners do not compete with eachothertosolveamathematicalproblem.Rather, the forgers use their cryptocurrency coins or stakes to perform block validation. The PoS process consumes less energy, incurs a lower implementation cost, and achieves faster processing time in contrast to PoW [15].
- *DelegatedProof-of-Stake(DPoS)*:DPoSholdsthepower of stakeholders for the approval of voters and resolving theconsensusissuesinanhonestandrepresentativeway. This consensus mechanism is designed to protect all the participants in a free, fair, and transparent environment. It is a fast, efficient, flexible consensus.
- *Proof-of-Capacity (PoC)*: It is designed for public distributed ledger and utilizes free disk storage as a resource.Also,itusesthespaceoftheminingnode'shard drive instead of its computing power. Consequently, it reduces energy consumption in POW, and exhibits the potentials to reduce the incentive of bitcoin hoarding.
- *(Practical Byzantine Fault Tolerance (PBFT)*in this algorithm, a new block is determined in a round. In each round, a primary would be selected according to some rules. It is responsible for ordering the transaction. The whole process could be divided into three phases: pre-prepared, prepared, and commit. In each phase, a node wouldenternextphaseifithasreceivedvotesfromover 2/3 of all nodes. So, PBFT requires that every node is known to the network.

B. SmartContracts

Smartcontractsareautonomousandfullypredictabletools withfeaturesofasoftwareagentinwhichpartiesareable to observe their performance, verify that the contract hasbeenperformedorbreached.Indeed,everysmartcontract

TABLEI
CONSENSUSMECHANISMSINBLOCKCHAIN

Energyefficiency	Mechanism	Timeprocess	Blockchaintype	Cost	Platforms	Applications
-	PoW	slow	public	high	Bitcoin,Litecoin,Ethereum,Iota	banking,energygrid, etc.
✓	DPOS	quick	public	low	Bitcoin,Ethereum	Electronicvoting
✓	POS	quick	public	medium	iota	e-health,telecommunication
✓	POC	slow	public	high	Bitcoin	Electricvehicle

hasauniqueaddress,andtransactionscontainingdatacanbe sent to that address to trigger the execution of the contract code.Hence,thenodesinthenetworkindependentlyexecute the code. The code and the trace of operations of a smart contract can be examined by all network participants and the trace is ensured using cryptography. Smart contracts enable the automation of complex multi-step processes and proper, distributed, heavily automated workflows. Finally, it should berunself-enforceorautonomousgovernanceapplications.

C. Platforms

Severalblockchainplatformsarecurrentlyindevelopment and use, each one is targeted for a specific use case.

- *Bitcoin:*it was the first to use blockchain and is subsequentlythefirstcryptocurrency.Itintendstoactas a decentralized electronic transaction system, in which individuals can store and transfer value between one another without the need for central authorities. The platformoperatesunderthePoWconsensusmechanism.
- *Ethereum:*it was introduced in 2013 to provide a platform for decentralized applications. It took the concept of blockchain and incorporated a turing-complete scripting language with it. This allowed for applications themselves to be stored inside the blockchain wherethey can be used by anyone connected to the network. Ethereum allows arbitrary code to be stored and executed inside the blockchain. Ethereum currently uses PoW protocol.
- *Hyperledger:* founded by the Linux Foundation in 2015 and it has grown rapidly in the last few years to reach morethan230organizationsasmembers.Thereasonbehind this direction is to offer more competitive features and capabilities, high-quality solutions. Also, it offers theabilitytocustomizeandfixbugs,throughaccess to source code and lower the total cost of ownership. HyperledgerFabricadoptspBFTconsensusmechanism.
- *Iota:*itwassetasacryptocurrencyfortheIoTindustry. Insteadofusingablockchain,itisbuiltupontheTangle, a mechanism that succeeds the blockchain. The tangle does not have miners, instead opting for a user-driven network;wheneveratransactionissent,thesendermust authenticate two previous transactions. As there are no miners, the computation required to run the network is significantly reduced, allowing nodes to run on devices with little computational power.

II. SCALABILITY AND REAL-TIME DEPLOYMENT

Due to the remarkable characteristics of decentralization, persistency,anonymity,andauditability,blockchainhasbeen applied to different domains, including content delivery network, smart grid, and data management systems.

A. IntelligentTransportSystems

Blockchain technology is popularly used in the Intelligent Transportation System (ITS). According to a recent survey [16],almost$140billionpaymenttransactionsareperformed for binding the daily agreement in the transportation system. Therefore, blockchain technology is necessary to improvethe transport industry through coordination of documents, approvals,fastercustomsclearance,reducedprocessingtime. Blockchain provides multi-fold benefits to the ITS in termsofcostreduction,improvedefficiency,andprovidingsecurity services to the end-users [17]. The work in [18] suggested that the security and privacy issues in ITS can be effectively handledusingblockchaintechnology.Theauthorsconsidered three phases of ITS, i.e., inter-vehicular system, gateways, andintra-vehicularsystemtoprovidesecureandefficientdata processing,networkmonitoring,privacy-preservingservices, and reliable data fusion. ITS domain includes smart robotic systems,unmannedaerialvehicles[19],vehicularnetworks [20]andtrafficmanagementmodules.

B. ElectricVehicular

Electric Vehicles (EV) are equipped with one or more batteriesalongwiththecommunicationinfrastructuretosupport information sharing among various peers. Various energy service providers support such services by providing realtimeenergy tradingplatformssuch asPlug Share[21].In the study of [22], a decentralized security model was proposed based on smart contracts using blockchain technology. This model provides an authentication mechanism between EVs and CSs based on four phases, i.e., registration, scheduling, authentication, and charging. [23] proposed a consortium-based blockchain technology to improve the transaction safety and security among Plug-in Hybrid Electric Vehicles without the involvement of a trusted third party. The authors designed a P2P Electricity Trading system with Consortium blockchain for ensuring secure energy trading. With security andtrust,theproposedmodeloptimizestheelectricitypricing and trading between EVs and CSs.

C. EnergyandSmartGrid

Intheenergysector,transparencyrequiresmanagingfunc- tions like billing, trading, marketing, smart grid, and grid management. As a blockchain solution, Ethereum platformis widely used in the energy sector. In particular, the authors of [24] propose a token-based decentralized energy trading systemwherepeersanonymouslynegotiateenergypricesand can securely perform transactions. The aim of [25] is to reduce the transaction limitation resulting from transaction confirmation delays on energy trade. For this, a credit-based payment scheme is proposed to support fast and frequent energy trading, where an optimal pricing strategy using Stackelberg game is used. The work in [26] builds a per- missioned edge blockchain to secure the peer-to-peer energy and knowledge sharing in their framework. To maximize edge intelligence efficiency, they investigate the wirelessly- powered multi-agent edge learning model and design the optimal edge learning strategy. Also, by constructing a two- stage Stackelberg game, the underlying energy-knowledge trading incentive mechanisms are proposed with the optimal economicincentivesandpowertransmissionstrategies.Inthe study of [27], blockchain technology was utilized to provide secure, reliable, and transparent energy trading transactions using a mobile charger billing system.

D. Healthcare

Healthcare is another sector where blockchain technology couldbeeffective.Theworkin[28]concernstheexploitation oftheblockchaininmanaginghealthdataandsharing them securely and privately, to either ensure anonymity and integrityacrossprovidersduringthelifetimeofapatient. In [29], patients connected in one platform are enabled to give access to their personal medical information for the doctors and healthcare providers for radiation oncology. In the paper [30], a demonstration of a monitoring system is introduced where the collection of personal medical dataand the notification of the patient in case of an emergency happeninreal-time.Further,theworkin[31]introduces a technique to incorporate WBAN with blockchain for se- curing electronic health records. Moreover, the blockchain provides authentication and authorization rules to validate eachtransactionwithinthenetwork.In[32],anovelplatform is proposed for monitoring patient vital signs using smart contracts based on blockchain. This system used a hyper- ledger fabric that provides several benefits to the patients, such as an extensive, immutable history log, and global access to medical information from anywhere at any time.

III. XAI FRAMEWORK

An example of an e-health platform involving blockchain technology is depicted in Figure 2. In this platform, the sensorsimplantedinthepatient'sbodysendapacketto thegatewaydevicedescribedasthepersonalserverinthe figure. The packets are then sent to the blockchain network, wheretheyareaggregatedandencryptedforperformingtasks and storing data. Blockchain data is sent to the medicalcenter to be decrypted and accessed by doctors that can get more queries about data and decrypted as a result. Then, the transaction is approved and the block is updated.

The technical analysis focuses on the features of the developed blockchain-based system, such as the applications of the developed system, the blockchain used, and the consensus algorithm used. The spatial analysis focuses on applications that are more popular in a specific country(ies) and/or region(s). Finally, the temporal analysis reveals the estimated timeline during which blockchain penetrated each healthcare research domain

A. XAI

1) The methodology emphasizes a structured pipeline beginning with high-quality data preprocessing, including normalization, missing value handling, and feature selection based on both statistical relevance and medical significance. Models such as Support Vector Machines, ensemble learners, and neural networks were employed to capture complex nonlinear relationships among clinical features like age, cholesterol levels, blood pressure, ECG results, and lifestyle indicators. The novelty of the approach lies in embedding explainability mechanisms—such as feature attribution, local explanation methods, and global model interpretation—directly into the decision-making workflow. These mechanisms allow clinicians to identify which features most strongly influence predictions, thereby aligning AI outputs with established medical knowledge.

2) Data Access Protection: Blockchain was also recog- nized as an authentication provider to verify user access for health-related data services using only one identity.

3) Data Sharing: in many healthcare implementations, blockchain technology, is at the forefront of many current developments, redefines data processing and governance. This is to its adaptability and unprecedented segmentation, secure and sharing of medical data and services.

B. Solutions

1) Resource Consumption and Computational Cost: in [35],theauthorsproposeanaccessprotocolthatsignificantly reducesthecomputationalburdenontheresource-limited

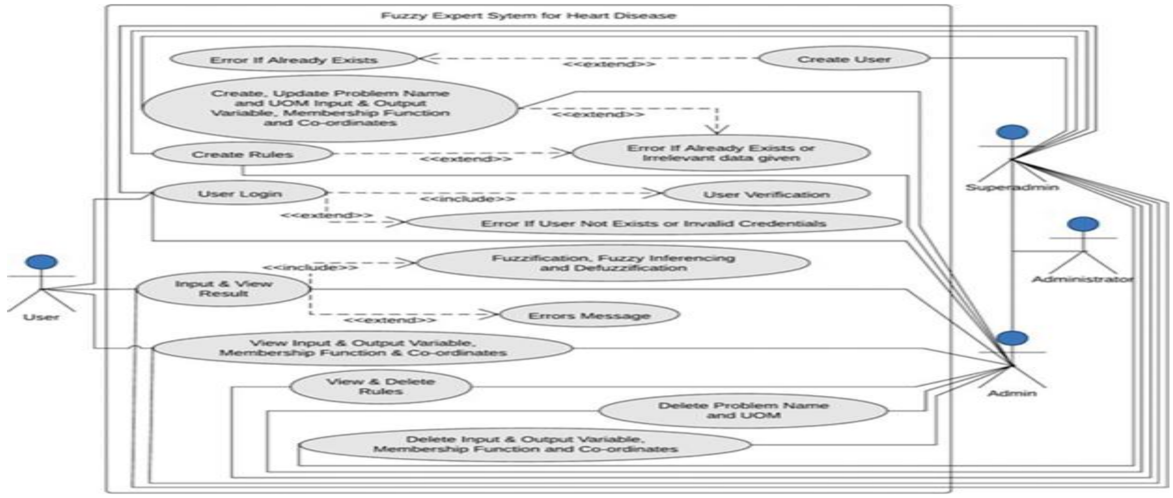

Fig.2.ProcessofdatatransmissionviablockchaininWirelessBodyAreaNetwork.

sensornodeoftheIEEE802.15.6std.theprotocolwhich is an improved display authenticated association. Using this protocol,nodescanagreeonamasterkeyaswellas theiraddresses.Evaluationresultsillustratethattheproposed protocolperformssignificantlybetterinbalancingoftemper- ature (to avoid damaging heat effect on the body tissues) and energy consumption (to prevent the replacement of battery and to increase the embedded sensor node life) with efficient data transmission achieving a high throughput value.

Thepurposeofthisstudy[36]istoachievestability andefficiencyintheroutingofWBANthroughmanag- ing temperature and energy limitations via blockchain-based AdaptiveThermal/Energy-AwareRouting(ATEAR)protocol for WBAN. The results show that by preserving residual energy and avoiding overheated nodes as forwarders, high throughput is achieved with the ultimate increase of the network lifetime using Castalia and Hyperledger Caliper. They have also presented an analytic model to study the performancesoftheminingprocessthathasahighimpacton the overall response time of the system. In their future work, they plan to go further in the implementation of the system and perform large scale tests with physical and virtual IoT devices

*2) DataAccessProtection:*In[37],theaimistoformulate secure and reasonably resource optimal algorithms with a robust key generation and management scheme in today's need. The two security suites for WBAN, which comprises on KBS keys, KAISC and Hash algorithm three improved versionsofkeymanagementproceduresandauthentication proceduresrespectively.Theexperimentalresultshaveshown the performance of the algorithm for the randomness of key and the execution time is much less as compared to the previously developed methodologies. With the help of the proposed schemes, the patient's health monitoring will be safer and beneficial for IoT applications.

*3) DataSharing:*Thepaper[38]presentedane- healthcare system based on blockchain integrated with WBAN, which provides security for patient data. The pro- posed system consumes fewer hardware resources while maximizingthedataprotectionlevel.Theremotemonitoring based on the blockchain offers data interoperability, where data are shared among different users of the system like pharmacy personnel, medical center, health insurance, and emergency service.

IV.CONCLUSION

This work presented an overview of This work presented a comprehensive Explainable Artificial Intelligence (XAI) methodology for heart disease classification, addressing a critical gap between predictive performance and clinical trust. While conventional machine learning and deep learning models have demonstrated high accuracy in cardiovascular risk prediction, their "black-box" nature limits real-world adoption in healthcare settings where transparency, accountability, and interpretability are essential. The proposed XAI-driven framework bridges this gap by integrating robust classification models with post-hoc and model-intrinsic explainability techniques, ensuring that predictions are not only accurate but also clinically meaningful and understandable to healthcare professionals.

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