Design and Performance Evaluation of a Blockchain-ML-NoC Integrated Decision-Driven Support System for Secure B2C Healthcare Applications

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ABSTRACT

This study explores the development and performance evaluation of a Decision-Driven Support System (DDSS) in a B2C healthcare context by integrating blockchain, machine learning (ML), and Network-on-Chip (NoC) technologies. With Ethereum as its blockchain, Flutter as its interface, Golang as backend processing, and wireless 3.5D mesh NoC data communication, the system achieved a high throughput (6 Gbps), robustness against link and node failure, and scalability. The interface allows real-time secure data processing, with more than 90% access accuracy, and reduced prediction bias (MBE reduced by 82.4% compared to EDIP). It demonstrates a more reliable, secure, and faster transactions of healthcare data. Theoretical implications are discussed, including the integration of technology and healthcare needs. In practical terms, it confirms that the system can be used in real life situations. The following limitations might occur regarding both blockchain scalability, ML adaptability and sustainability. Further improvements include self-optimizing NoC systems based on AI, low-power design, merging with future technologies such as quantum computing.

Keywords: Blockchain, Machine Learning, Network-on-Chip (NoC).

I. INTRODUCTION

Big Data always cites the enormous amount of data generated from different sources. Conventionally, it is beyond the processing software to interpret and organize. Information comes in various forms, such as unstructured, structured, and semi-structured data, from many sources; examples are social media, business transactions, sensors, and devices connecting the IoT. Big Data is not just about the volume of information but also the data velocity and varieties at which the data is generated and processed. The boom of Big Data has been fueled by the endless stream of digital data that people have produced and the technologies that have enabled people to store, maintain, retrieve, and analyze such data. This change is reshaping the way enterprises do business, not only by improving efficiency but also by facilitating new ways of impacting value. Big Data plays a significant role in making this digital transformation possible—an area where things are remolded in a different format and information that was not attainable before it was available. One of the main factors that distinguish Big Data is its size/volume. Data generated by various companies, individuals, and web-enabled devices is huge and still increases at an unmatched pace. This growth has been made more accessible because of social media, the internet (including mobile phones) and the massive digitization of business bookkeeping and standard processes. While diversity is the most essential factor for large data, it refers to the variety of information types that are collected and analyzed. Data can be presented in different forms, including structured data, like databases holding numbers and names, and unstructured data, like images, texts, and videos. This variety pushes an organization to find the best strategies for storage, maintenance, processing, and future analytics since more than traditional databases and software tools may be needed to handle the complexity of Big Data. Data speed, or the ever-growing amount of data that needs to be collected, stored, maintained, and evaluated within very short periods of time, is another clear-cut defining factor. Short-term or sometimes instant information processing is becoming unsurpassed in different activities, from online fraud detection to real-time traffic direction and instant personal recommendations on digital platforms. The actual statement expresses the idea of the authenticity and certitude of reported data. Big Data often involves defective, incoherent, and unreliable data, which poses the highest level of challenges in the analysis phase. Considering these challenges, implementing strategies that will ensure the reliability and accuracy of information analytics is critical for organizations and enterprises that utilize Big Data as a primary tool for strategic decision-making. This is because Big Data's values stress the importance of converting Big Data into practical information as well. Big Data is the main feature of data analytics, and it is about the volume of data. The value of big data can be found in using the data to make better decisions, improve operations, develop new products, and gain a competitive advantage. While extracting worthwhile insights from extensive and different datasets may require tools with advanced analytical functions like machine learning and artificial intelligence, these instruments must be highly sophisticated. Eventually, among many other things, Big Data will become a complex and multifaceted phenomenon that will no less than create a radical shift in how data is handled and employed. Its consequences, though, are widely reaching, embodying everything users know of in socioeconomic and societal life. With the technology progressing at a more excellent pace, grasping and applying the power of Big Data becomes the key to differentiating thriving businesses and those that tide over time in the global market.

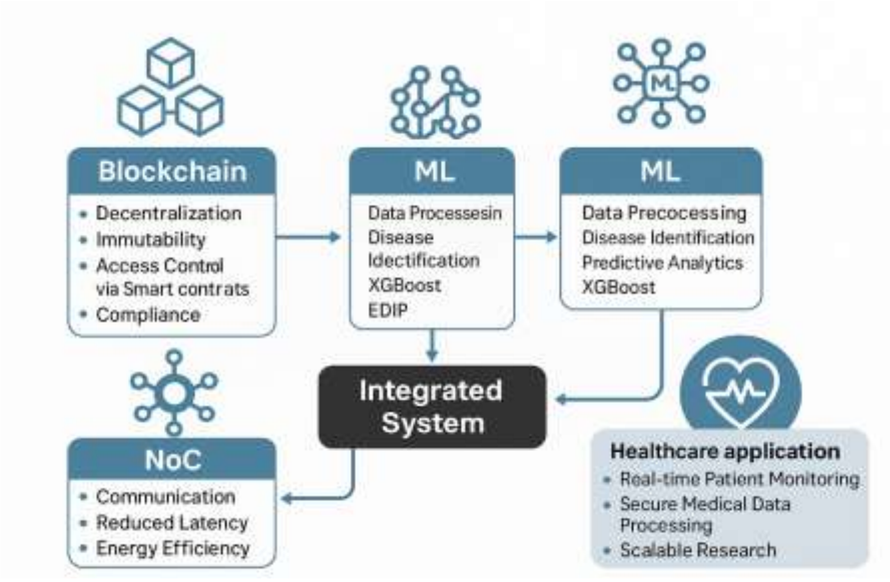


Figure 1: Integrated Framework of Blockchain, Machine Learning, and Network-on-Chip (NoC) for Secure and Efficient Healthcare Applications

This infographic illustrates a holistic architecture that integrates Blockchain, Machine Learning (ML), and Network-on-Chip (NoC) technologies to enhance healthcare data security, processing, and real-time analytics. The framework highlights Blockchain's role in decentralization, immutability, and smart contract-based access control; ML's function in disease identification and predictive analytics through models like XGBoost and EDIP; and NoC's contribution to efficient intra-system communication and low-latency data exchange. All components converge into an integrated system that supports critical healthcare applications such as real-time patient monitoring, secure medical data handling, and scalable research support.

II. DESIGN, IMPLEMENTATION, AND EVALUATION OF THE DDSS MODEL

2.1 EXPERIMENTAL SETUP FOR DDSS IN B2C ENVIRONMENTS

The experimental set-up for assessing the DDSN in support of the B2C community environment focuses on several technical and building blocks. The main driver of the behavior is where each part assumes a vital function to guarantee the system's excellent performance, security, and usability. Table 1 presents a detailed parameter list of DDSS for empirical configurations.

Table 1: Experimental Configurations for Evaluating DDSS

Configuration Components	Descriptions
Platform	Ethereum
Front End	Flutter
Back End	Golang
Host	Infura
Server	Jetty
Integrated Development Tool	Truffle
Ram	8 GB
Language	Solidity
Hashing	SHA-2
Storage Type	Decentralized

The Ethereum platform is the core crypto blockchain execution support for the research. At the heart of it is the decentralized environment, where smart contracts may be created and executed. Such contracts would be implemented by executing the conditions previously defined in the e-business transactions and, because of their operation could be applied in the B2C field.

The Desktop Application Interface is constructed using Flutter widgets. This interaction is important in a B2C setting for customers that are dragging the light inter-processual system. Flutter is a platform for developing applications to work on any device. So, the DDSS works with all your devices.

Backend services, leveraging the efficiency and scalability of Golang. It works with business logic, data processing, and interfacing with the Ethereum blockchain handled by smart contracts.

Infura is what people use to hit the Ethereum network without having your own private node. It offers robust, scalable and intuitive infrastructure, which could establish its interaction to the blockchain.

Jetty is commonly seen as a lightweight web server and servlet container capable of a lightning-fast start. It handles the clients' HTTP requests and the servers' responses in both ways, so the communication between them is in fact fast and secure.

Truffle provides functionality for smart contracts. It provides an environment where smart contracts can be developed and tested more quickly and a way for them to be deployed as an asset on the chain. This system is backed with an 8 GB to allow you to run applications without any difficulties and to delegate the handling to a couple of processes at once.

Smart contracts on the Ethereum blockchain are written in Solidity. The only reason it's been chosen is because it's convenient and EVM friendly.

SHA-2 is an algorithm used to check deliveries when testing the integrity and authenticity of data. This gives transactions credibility in the B2C world.

The storage service is decentralized to the infrastructure and is synchronized using the blockchain. It guarantees data availability and service, enhances data security, and mitigates threats of centralization.

The DDSS's performance is assessed using various metrics: The DDSS's performance is assessed using multiple metrics:

- Processing Time: They are measured by uploading and downloading the contract file to evaluate the system's speed.
- Throughput: Evaluated through Data Transactions, Access Transactions and Validation Transactions to understand systems capacity.
- Data Accuracy: Checked transaction content-wise to pick the corrupted data and look into the correctness of transactions.
- Vulnerability Measures: Tested to demonstrate the confidentiality and security of the transaction data, indispensable in B2C interaction.
- This integrated experimental design and assessment strategy gives a complete picture of how the DDSS operate within a B2C scenario, emphasizing strengths and listing areas for improvement.

2.2 Design and Architectural Considerations

With the aim to meet the complex demands of healthcare that go beyond big data, we propose an advanced system that integrates blockchain, ML, and NoC technologies. This was an ingeniously devised system to guarantee high level of data security, accuracy and awe-inspiring efficiency which ushers in a new era where computerization becomes a paramount factor in modern healthcare, ensuring a future with better healthcare.

Blockchain technology is pivotal in a world where data is securely locked away. This is a key feature of an integrated system. The key to the security function of the blockchain lies in its decentralised structure as data is not stored in a central repository but distributed among every node in the network meaning that the security of the entire system cannot be compromised in the case of a broad spectrum of attacks and data loss originating from a single point. The immutability of information in blockchain chains ensures that data cannot be modified or modified in any way; otherwise, it can be tampered by a malicious party. This is to maintain a reliable and clear record. Automated access control is available through smart contracts, enabling a transparent and secure access to use them for managing and controlling user data permissions. This is necessary to maintain patient privacy and organization's regulatory compliance. The most sensitive information of patients is secured with state-of-the-art encryption methods, making sure that it can only be accessed by qualified individuals.

The data is analysed using ML al-gorithms. These algorithms, particularly advanced ones such as XGBoost, EDIP, etc., can further be applied in evaluating healthcare data because of their high accuracy. Before the analytical work can begin, several data preprocessing steps must be taken, including data cleaning, normalization and converting the data into the right format for follow-up analysis. The ML models then continue to search for the correct pattern, or in this case the anomaly in the data to assist in disease identification which is a major aspect of diagnosis and prognosis. The system needs to be shaped so that it continuously tests and maintains the AI algorithms operating correctly in condition to provide with high accuracy and reliability in life data analysis.

It is the NoC architecture, hence, which is a part of the system that speeds up as well as optimizes the communication of the ICs within the system. What will have been the decade of digitization will be underpinned by a scalable NoC architecture. The architecture is based on low-latency on-chip communication between IP cores. It could therefore be used for real-time health data processing and analysis. Secondly, energy saving is one of the foremost requirements in design of NoC implementation, where NoC IP should attempt to reduce overall energy consumption of the system in particular in portable medical devices.

NOC and ML and Blockchain technologies will be collaboration if the coordination between them is smoother to offer continuous operation. In the design of the MPC, the data flow control is the basic rule to follow. There is need to address the data flow problem between blockchain networks, the global ML processors and NoC. This coupling should emphasize security and privacy provisions and, therefore, effective mechanisms which help to mitigate data security for storage, transmission, and processing. Tools that monitor and manage performance, data integrity and security in these areas can provide an early red flag in these exposed situations to help work+frame through them.

The benefits in the health sector are obvious, as this ties in with health practitioners ability to identify and treat diseases better. In addition, the hybrid use of EDIP and XGBoost models will separate the cancer types and chronic diseases using various data from healthcare records, picture and Internet of Things (IoT) data. Thus, real-time patient monitoring is facilitated with this system application as it can instantly read the data carried by IoT devices and results in healthcare professionals receiving the information in real-time regarding the health condition. Table 2 Summary of the major design parameters for a blockchain and ML integrated medical data storage and processing system with support for NoC.

Table 2: Vital Design Components of the System

Design Component	Parameter
Blockchain	Decentralization
	Immutability
	Access Control
	Data Encryption
	Compliance
ML	Data Processing
	Model Accuracy
	Training Time
	Model Optimization
NoC	Architecture
	Latency
	Energy Efficiency
	Communication Protocol
Integrated System	Data Flow Management
	Security
	Monitoring
	Scalability
Healthcare Application (Future Direction)	Data Types Supported
	Real-time Analysis
	Research Support

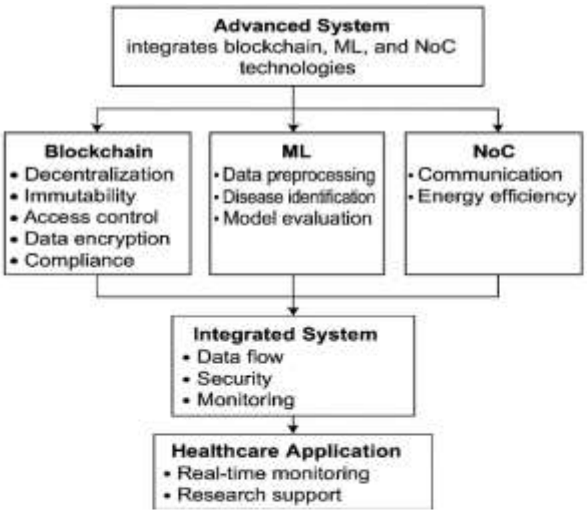
Besides that, research is squarely on the advantages of this system, where robust data analysis is offered, and researchers can develop new treatments and therapies. The performance of the integrated system's powerful data management and analysis capability contributes to rapid decisions and medical progress, since deep data analysis of large dataset is allowed.

From a technological point of view the system needs to be supported by a solid hardware and software structure. Hardware development Hardware to meet stringent performance requirements, which may must be achieved as high speed space contain fast data storage and data read supper. The software will also need the capacity to accomplish complex data processing and analysis, while all of this is going on. The scalability is critical in the system as the health-related information is increasing and there are multi-rating capabilities of medical research and clinical treatments. In view of the future, architecture would have to be adapted to be more flexible in responding the newest technology and adjusting in response to the ever-changing healthcare need. Accordingly, ongoing development of machining learning-based algorithms and NOCs at the system level will also improve system performance and efficiency. The introduction of numerous new data sources, such as genomics and personalized medicine, in addition to the already wide repertoire of sources, will extend the spectrum of where the system can be deployed within healthcare.

2.3 Implementation Challenges and Solutions in Blockchain-ML-NoC-Based Healthcare Systems

Integrating Blockchain, Machine Learning (ML), and Network-on-Chip (NoC) in healthcare systems brings promising solutions but also presents significant challenges. However, one problem is volume of the contracts file size that can slow transaction. More efficient proof of contract protocols and optimal consensus mechanisms such as PoS and DPoS also mitigate execution lags. A further obstacle is transaction throughput, which is crucial to sustain system usability when data is flowing at a high rate. In order to address this challenge, scalable NoC architecture have to manage the dynamic bandwidth allocation. It’s important to make sure transactions are not ambitiously consumed, particularly in the healthcare space where transactions need to be accurate. The use of concepts, like cryptographic hashing and digital signatures, ensure the safety of data and facilitate blockchain’s transparent and immutable ledger. Security is still an issue and requires for continuous assessment of vulnerabilities and penetration tests. ML improves this by warning about threats and activating early protection systems. In the end, good engineering for throughput estimate, transaction validation and enterprise-level cyber-threat protection is what is needed to pull this off. Through overcoming these challenges, the system can provide a secure, scalable, efficient infrastructure for the management of sensitive healthcare data and to support decision making. This seamless integration promotes the reliability and efficiency of digital healthcare solutions.

III. PROPSOED FRAMEWORK



The proposed framework integrates Blockchain, Machine Learning (ML), and Network-on-Chip (NoC) technologies to address the complexities of modern healthcare data systems. Blockchain ensures decentralized, immutable, and encrypted patient data management with smart contract-based access control. ML models like XGBoost and EDIP perform accurate data preprocessing, disease identification, and predictive analytics. NoC enables fast, energy-efficient communication between components, ensuring real-time data flow and reduced latency. This integrated system supports real-time patient monitoring, secure medical data processing, and scalable healthcare research. Together, these technologies ensure high accuracy, security, efficiency, and innovation in healthcare delivery and clinical decision support systems.

IV. EMPIRICAL CONFIGURATION OF EL

The hyperparameters for the ensemble learning approach, specifically utilizing EDIP and XGboost, have been fine-tuned to achieve optimal predictive accuracy for large-scale medical data analytics. The k-NN algorithm in the EDIP is set to a value of k=5 and balances between overfitting and underfitting in choosing the number of nearest neighbours. The parameter δ, which defines to the algorithm the size of the training subsets in EDIP, is usually smaller than the full set of data and should be selected experimentally to have the best compromise between representation of the statistics and computational cost. A learning rate of 0.1 is fine for xgboost in terms of convergence time and meantime training stability. We use 500 estimators, so that the model can be learned with complex patterns and without becoming extremely expensive to compute. A limit of 6 for the maximum depth of trees avoids over-fitting the model but still allows to learn the complexities of the data. A row sample by tree value of 0.8 ensures that each tree is trained on a random but broadly representative subset of data, and a column sample by tree value of 1 specifies no sub-sampling of features when growing each tree, using the full feature set for maximum learning. The regularization hyperparameter ν is chosen as 1 (1 e) to regulate the model smoothly. Finally, the updating rate of residuals, θ, is set to be 0.1, to make the combined new trees to correct the mistake on the previous trees on an accelerating rate without growing too fast. Such hyperparameter values are in fact the result of an empirical tuning to achieve highest performance on the medical datasets being analyzed, as the high accuracy values in these studies testify. Table 3 shows the list of hyperparameters.

Table 3: List of Vital Hyperparameters

Hyperparameter	Optimal Value
k (for k-NN in EDIP)	5
δ (for EDIP training)	Determined experimentally
Learning Rate (for XGboost)	0.1
n_estimators (for XGboost)	500
max_depth (for XGboost)	6
subsample (for XGboost)	0.8
colsample_bytree (for XGboost)	1
Ȥ (regularization hyper-parameter for XGboost)	1
ϑ (for updated residuals in XGboost)	0.1

4.1 Evaluation Metrics of EL

Error Metric Indicator (MAE) constitutes a fundamental tool that concerns the average magnitude of the differences between the outcomes that the model and the actual observed outcomes predict. The equation displays the formulation of MSE. The MSE is estimated by averaging the squared errors: the square difference between the predicted values ($\hat{P}_i$) and the observed values (E_i) for all k data points in the dataset.

$$\boldsymbol{MSE = \frac{1}{k}\sum_{i=1}^{k}(E_i - \widehat{P}_i)^2}$$

The use of MSE in this research is particularly crucial due to its impact on larger errors. Especially in the medical field, large errors to the truth can be very undesired. As a result, by lowerizing MSE when training ML models, researchers typically hope to build more accurate and robust models that are suitable for complicated and sensitive healthcare benchmarks (diagnosis, treatment planning, patient monitoring).

The RMSE, an important indicator in the evaluation for prediction models, is very accurate in the medical field. It is an indicator of the average error between predicted and observed values. Calculated as the root of the average of the (squared) differences), the RMSE is an important source of informat ion about the quality of the model ts, wh ich ensures the belief in the model t results. Formula (6.5) presents the standard definition of RMSE.

$$\boldsymbol{RMSE = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(E_i - \widehat{P}_i)^2}}$$

The RMSE is the preferred metric in many modeling scenarios due to its heightened sensitivity to significant errors. It’s a sensitivity that’s particularly helpful in medicine, where the price of a serious error can be insufferable. It punishes large deviations much further compared to those in MAE and therefore it can measure when, although there are few times that the model is horribly off its prediction, those are very important. In this study, RMSE will be used as a sound reference to assess all models attempted (which justifies its significance).

If the model's residual has residual-driven errors that could possibly result in a large RMSE, it could be a small model that has fewer residuals that probably will be inflated for scale. It is therefore useful to use RMSE in conjunction with other All of the above indicates that RMSE, in isolation, does not provide sufficient information for a complete picture of model performance. Additionally, RMSE is preferred over the real values, with which analytical calculations are performed with the real values, if they cannot be used when there are different data sets.

The MBE criterion quantifies the mean tendency of model's prediction to over or under predict observed values. It formulates the average mean error for each of the k data points, predictions (y_i) and actual (x_i), which is expressed as,

$$\boldsymbol{MBE = \frac{\sum_{i=1}^{k}(y_i - x_i)}{n}}$$

A positive MBE value indicates that the model would overestimate the actual result, while a negative MBE implies that it would underestimate it. In data analytics pursued in medical domain, such as the one for this research where making a more accurate prediction can lead to significant differences in patient outcomes, MBE has a role to play in automatically identifying systemic bias in the predictive models. For example, if a blood pressure model overestimates BP values all the time, MBE would be positive, indicating the underprediction bias.

However, because of MBE, models’ over- or under-projection (either positive or negative) bias is revealed. However, it doesn’t give you the full picture of accuracy of a model as it does not show magnitude of errors — only the direction of the errors. Moreover, a small to be a high accuracy of the model Please cite this article as: Zinedine MY, et al. A combined data and knowledge-based approach for model-based fault diagnosis with application.

Therefore, MBE remains an important diagnostic indicator of bias, but it is typically combined with other metrics which provide information about the scale of errors and are not mutually cancelling. Bias detection and rectification is a critical element in building and validating predictive models in health care, as it can improve the reliability and credibility of model predictions, however this is the primary function of the MBE. It suggests that researchers and practitioners should amend their models accordingly so that the models are pulled closer to the zero line of MBE, where the model makes bias-free predictions.

4.2 Impact Assessment of EL on-Healthcare Data Analytics

Table 4 compares the performance of all learners as observed in terms of accuracy, MAE, RMSE, and MBE.

Table 4: Comparative Performance Analysis of EDIP, XGboost, and EL Methods across Four Medical Datasets

Methods	Diseases				Metrics
	BC	LC	HD	DS	
EDIP	98.12	97.24	94.16	91.1	Accuracy
	0.18	0.17	0.33	0.15	MAE
	0.12	0.09	0.07	0.13	RMSE
	0.072	0.089	0.089	0.067	MBE
XGboost	96.17	97.1	95.14	90.34	Accuracy
	0.18	0.11	0.21	0.09	MAE
	0.14	0.07	0.06	0.07	RMSE
	0.08	0.045	0.07	0.053	MBE
EL	98.43	97.47	96.34	98.14	Accuracy
	0.086	0.08	0.076	0.056	MAE
	0.089	0.056	0.023	0.03	RMSE
	0.034	0.027	0.04	0.031	MBE

Figure 2 illustrates the differences in the accuracies of three different machine learning methods, including EDIP, XGboost, and EL, for datasets labeled BC, LC, HD, and D_S, respectively. The results, while showing some volatility in the reliability of the EDIP classifier, underscore the importance of the EL method's performance. While the EDIP classifier demonstrates good tolerance in certain cases, this is not universally applicable. The XGBoost classifier, known for its strength, surprisingly displays the lowest precision value for all the datasets. However, the combination of XGboost with EDIP under the EL framework showcases a significant performance improvement across the majority of the datasets, leading to the highest accuracy level across all datasets.

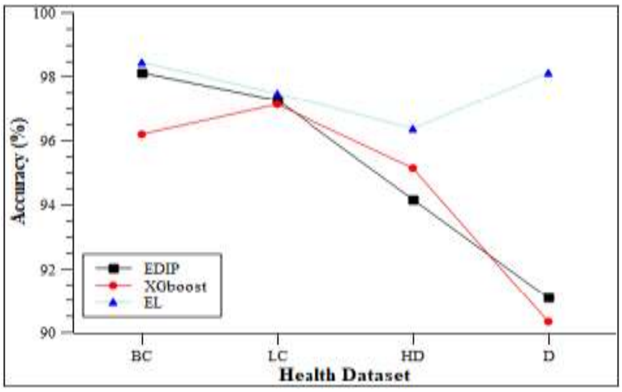


Figure 2: Comparative Evaluations of EDIP, XGboost, and EL in attaining Optimal Accuracy

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The EL method, a testament to the power of synergy, creatively harnesses the predictive capabilities of both EDIP and XGboost. It not only leverages the complementary of the two pair of methods, but also overcomes the weakness by combing the advantages of both of them into an ensemble method. It indicates that ensemble applying them improves the quality of model, as the trend is linear. The complementary role of the EL approach is most clear in the DS dataset, where it largely outperforms both single methods.

This increase in efficiency suggests that the EL leverage the data to capture and then exploit the patterns which are inherent to data for instance avoiding variance and bias from EDIP or XGboost is minimized. The obtained results are a testament to the fact ensemble methods, being comprised of different models, could perform better than individual algorithms, particularly on complex tasks such as medical data analysis, where the adequacy and accuracy is very essential for proper disease diagnosis and treatment.

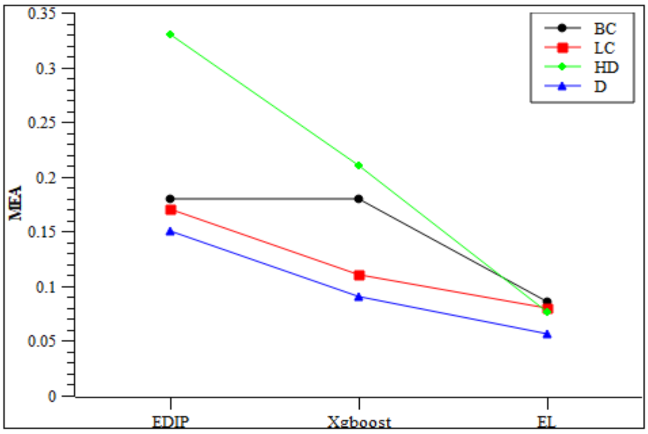

Figure 3: Comparative Analysis of EDIP, XGboost, and EL concerning MAE

Figure 3 showcases the MAE of three machine learning methodologies—EDIP, XGboost, and an EL model across four health-related datasets: About BC, LC, HD and Ds. The result shows the EL model is more accurate because of the lower MAE as compared with the other methods.

The discrepancy in MAEs of the EDIP, XGboost and EL models is not only a statistical issue but also a considerable practical point. The EL model with an MAE ¼ 0.0745 is significantly better than EDIP (0.207) and XGboost (0.147). Such qualitative difference is exactly reflected by the mean fold error being 94.13% and 65.76% lower than those for EDIP and XGboost, respectively, which demonstrates better accuracy in the EL model.

Noting a discrepancy of such size is important in the realm of health care where even small errors can have profound impact on patients and their treatment. The decreasing lines that finally resulted in the uppermost MAE values of the EL holder models indicate that the hybrid algorithm can improve such performance by shrinking the model further. Through mixing the powers, these controls of each power can be enhanced and compensated by the weak point in each power, leading to a more powerful generalizing strategy that can be generalized to several types of biomedical data.

The results given in Figure 4 are indicative of the validity of the EL approach in this study. The EL model for generating highly reliable predictive analytics is vital to disease diagnosis, treatment, and patient care, and reflects the important value of the model in the field of health.

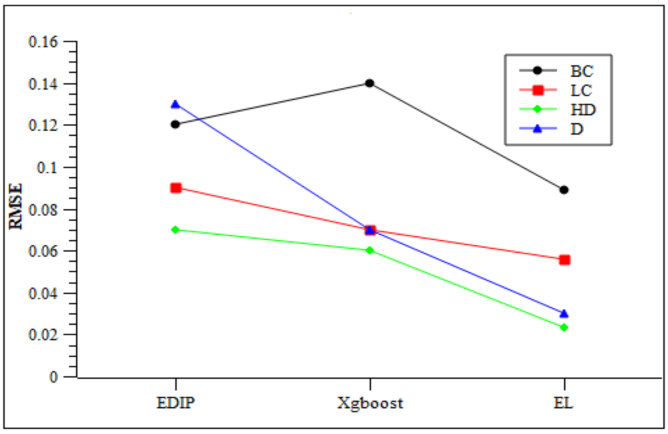

Figure 4: Comparative Analysis of EDIP, XGboost, and EL concerning RMSE

Figure 4 compares the RMSE of ML models for four health observation datasets. RMSE is a vital measure of predictive model accuracy that allows us to examine whether the model's predictions are satisfactory, especially regarding the magnitude of errors.

The EL model consistently outperforms the EDIP and XGboost models across all datasets, as evidenced by the significant decrease in RMSE. Not only it is strong evidence for the ML model being more accurate, but also it can pinpoint exactly what types of true value issues the prediction faces. In particular, the RMS index of the EL code is registered as 0.066, and exhibits a novelty of 69.73% comparing with EDIP method and 52.78% with respect to XGboost code. These proportions visually illustrate the difference in accuracy between single and ensemble modeling, or how bias is reduced in predictions.

The line graph reveals that the EDIP model -- despite presenting the better results in the most datasets -- has the biggest RMSE in one of the datasets, the fact that may indicate its specific constraints or may be disproportionately biased in that failure. In the case of EDIP, among the four models, RMSE is the lowest but still no better models than the EL model although the ELmodel is the best. Therefore, the advantage of the ensemble method is that it can take advantage of the rich set of possible choices that can be made with the different models and thus lead to an overall improved prediction accuracy.

Specifically, in clinical data processing, the average accuracy with low error rates is very important, as anything which slightly tends to be an improvement will have a significant effect on the treatment and the clinical results. The capacity of the EL model generating the lowest RMSE values presents great potential in medical practice, as medical staff can treat it as a aid tool, with which medical workers can get more accurate and reliable decisions or treatments, excluding the chance of misdiagnosis, and misadventure. Our result suggests that applied EL is an innovative method to forecast healthcare data analytics.

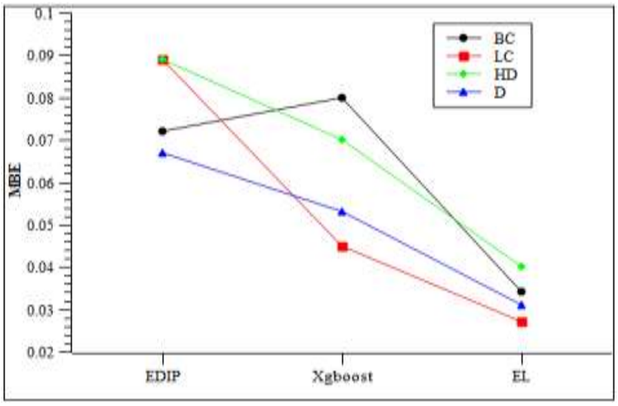

Figure 5: Comparative Analysis of EDIP, XGboost, and EL Concerning MBE

Figure 5 shows the MBE outcome of three ML models applied to the four health-related datasets. MBE stands for modeling bias, which is one of the factors causing systematic inaccuracies in predictive modeling. A positive MBE makes a model prone to overpredict, while a negative MBE suggests underprediction.

This result, shown in Figure 5, demonstrates the concept of classical MBE has more scores for EDIP and XGBoost techniques than for the EL method for all datasets. This comparison indicates that although both EDIP and XGboost have biased results in the prediction to some extent, the weighted solutions like the EL approach could achieve smaller MBE at the prediction level. In EL model bias, down value made to get below 82.40% of EDIP of estimates, 61.02% below XGboost.

This result points out that the EL model is a synergetic combination of the individual models' various predictivity and as a compensating impact, the biases of the individual models are not prevailing. The EL method enjoys the essential properties of each approach in a harmonious way that masks their defects, and can also be expected to produce less biased estimates toward the true values of the parameters of interest. This suggests that the EL model is prone to unsystematic over- or under-estimation vis-a-vis the datasets it operates over specifically.

In the sensitive domain of healthcare, where rightness and security are paramount, unsullied forecasts are important in diagnosis and treatment. And the prediction of the EL model is more accurate with smaller mean absolute error. The result indicates that it's not just the results accuracy that is enhanced using ensemble method, rather that it becomes certain that everyone could rely on the doubt-free and balanced result, which is an important issue in medical diagnosis based on predictive analytics.

4.3 Results Analysis of DDSS and Performance Benchmarking

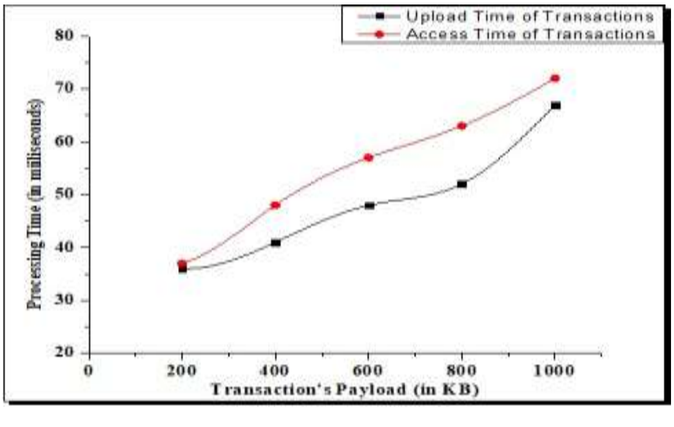

Figure 6: Processing Time of Contract File during Transactions

Figure 6 explains the interdependence of transaction payload size, uploading time, and accessing time in the B2C transaction process driven by blockchain technology. The execution time, shown, depends on the size of a transaction copy, and it is consequently an essential factor of scaling and productivity for blockchain systems.

However, it's evident that the payload sizes follow an increasing trend, leading to higher processing times. This is due to the need for more complex computational tools for data handling, encryption, hashing, and digital signature validation with larger payloads. What's more, the transit time of transactions reflects the overhead time of the upload delay, with the latter ahead by a little bit, but the difference doesn't increase with payload size. That means the time cost for accessed TXs (with extra validation and consensus among peers) is much higher than the information uploading.

The findings demonstrate the mediating pays of transaction activities on networking relationships. It indicates that the speed of peer connections can have great impact on the response time, especially when the number of peer memberships increases. In a distributed blockchain system, the confirmation protocols become complicated and so does the time taken to make a transaction, in terms of the number of nodes needed to confirm.

However, due to determinacy such as payloads, the mission must be made more robust. The restricted payload issue is, not a restriction to the larger volume and not a processing time over 75 % of the observed maximum, as the system efficiency remains so at significant limit. This is particularly important in the B2B case where it can slow transaction times, a bad thing in most cases but particularly apparent during user interaction and overall system throughput.

On a practical basis, the planning scheme is also robust, able to deal with some high transaction payload while not suffering a similarly dramatic increase in processing time. As a result, this is a basic feature of any blockchain technology, as it is too is expected to support the potential transactional activities of all sizes, and they do vary across the levels of complexities and the demands stemming from the B2C transactions.

The processing time is not only related to the end user's query or request as the user can make higher priority transactions that have to be processed as well to the processing time. That describes the degree of responsiveness of the system to user actions and the extent to which system performance is acceptable in client-centric applications, which is a characteristic of the system, creates a desired level of service.

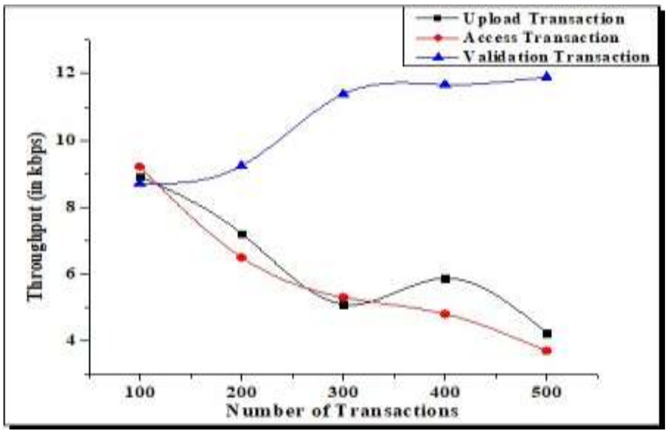

Figure 7: Throughput Estimations

Figure 7 shows an analysis of the work speed in a blockchain-based development, which will be used as a base for the B2C work. The trials will produce figures that directly confirm the system's speed in dealing with trades.

In order to do that, we are able to get the system's pattern for every 500/5000 cycles, which reveals how it processes the incremental rise of the load. In B2C, throughput is a significant performance metric as the more transactions can be performed with a system, the whole can be improved.

The complete overview of SC’s category can be indirectly seen in figure 7. It is worth mentioning the three most common operations at blockchain level are upload, peek, and validation transactions. Further examination on this figure shows that although the throughput of upload transactions is relatively flat as the number of upload transactions grows, that of validation transactions follows another pattern; These types of transactions, validations in particular, present a problem because they can produce long messages. The problem compounds if multiple transactions are cleared.

But this makes the net unusably heavy at times, slowing up confirmations, especially in big transactions such as validations and uploads, which take much longer then regular transactions. This increase in the number of transactions involves an increase in computational load for Hashing, Data validation and Consensus protocols which are more powerful and time consuming than developing and the validation however with not much con by parallel operations by parallel processor with more computational load. This results in longer transaction times, and ultimately means a reduction in the total number of registered transactions per second.

The salient feature of the system is that high levels of confidentiality and security are able to be preserved. Confidentiality is a key factor in a B2C system which includes many transactions involving huge customer data, and in a B2C system in which customer interaction is central. -- but apparently, there is a trade-off of the speed of the throughput. As the network grows and the number of transactions increases, the privacy vs. scalability trade-off becomes increasingly severe. The safeguards of the system and the secrecy all are fine, but only a system that is more superior can recognizer and manage the stacking load of transactions with performance validity.

Those issues can probably be solved by refining the process, with faster consensus algorithms, able to handle more transaction at a time or parallel processing hardware that won't be overloaded when doing the uploads and validation. Additional use of sharding methodologies or off-chain methodologies could also reduce the network's computational burden.

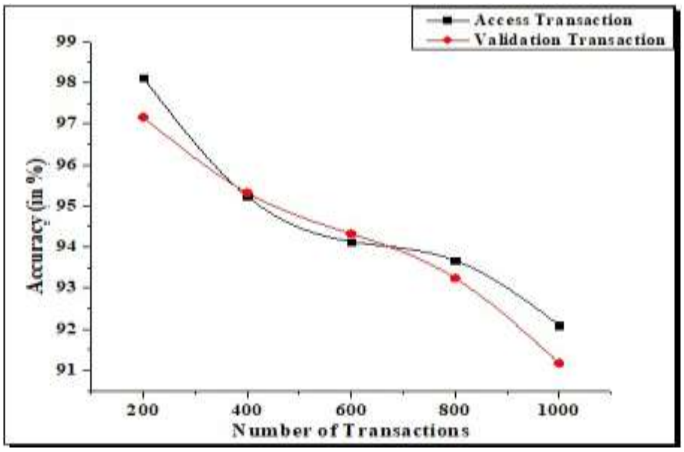

Figure 8: Transaction Integrity Assessments

Figure 8 evaluates the integrity controls within a blockchain-based B2C system, illustrating the validation and access accuracy percentages entailed in these transactions. The outcome shows how the accuracy trend depends on the platform's number of transactions.

The accuracy evaluation depicted in Figure 8 shows that even with the massive, diverse and changing datasets, the access and validation activities are responsible for more than 90% of proper data transmission. While the lead to the accuracy degradation of both transactions deteriorates with the transaction volume, it is only visible in the volume case. The system's ability to maintain transaction integrity is evidence that it is resistant to disruption. At the same time, accuracy still decreases with the increasing all volume, the transaction volume it can support.

This kind of trend can be attributed to multiple reasons such as maturation of the computational load with more hashed blocks and the complexity of managing a network with an even larger blockchain ledger. These are parameters that could affect the speed and the accuracy with which the transactions get validated and, consequently, perhaps the quality of the system's integrity checks.

Nevertheless, the network remains highly resilient to unauthorized modifications, as Merkle root provides the platform with an immutable memory, and the Merkle root feature is a criterion for validating the integrity of messages. To maintain or get more accuracy as the system scales, the optimization can be extended to consider the following criterion:

1) Improving the hashing algorithm.
2) Designing the blockchain data structure more.
3) Adding more layers of verification to overcome a high volume of ethical transactions.

Figure 9, a crucial representation, showcases the vulnerability index for a blockchain-based B2C system. It's a key metric that differentiates two types of attacks: Smart Contract Attacks and Transaction Verification Mechanism Attacks. The vulnerability index, a value of utmost importance, assesses how swiftly the system will respond to identified security threats.

The result starkly demonstrates a direct correlation between the surge in the number of transactions and the vulnerability indices. This is a concerning trend, as the vulnerability of each type of attack escalates in tandem with the transaction volume. This trend potentially exposes the system's diminishing legacy security functionality, a risk that amplifies as the transaction volume expands.

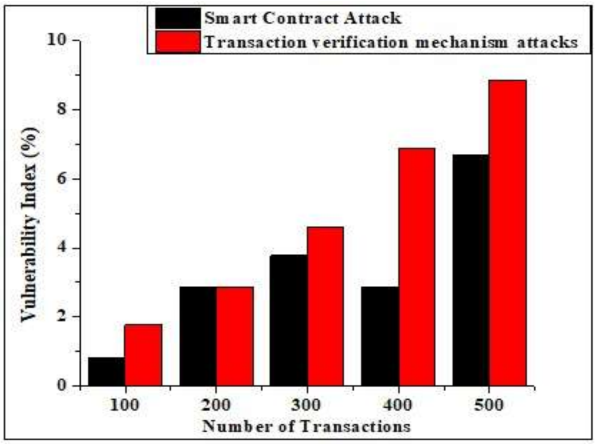

Figure 9: Analysis of the Vulnerability Index

Increased percentage-wise exposure would mark the rise of the vulnerability index; however, the value remains below the 10% threshold. This evidence, therefore, demonstrates that even though the number of potential intrusions increases, when the system has more transactions, the system continues to be secure in terms of limiting the number of accepted intrusions.

It isof vital importance that the vulnerability score be kept within a predetermined safe zone. This is of utmost importance in the B2C sector, as trust and thus transactions within the market depend on confidence and security.

The growing alignment of the fragility index and the number of transactions means there is a need for the security system that can be able to cater for those very high volumes. These systems help keep up the overall integrity of the system. That could be by scaling up the original blockchain infrastructure, optimising the smart contract code, tightening up the transaction validation methods, or applying more advanced cryptographic methods, which can help the system in an ever-changing cyber security environment.

V. SUMMARY

This paper directs attention to an existing DDSS designed to facilitate adequate data security in the B2C service primarily related to healthcare applications. We have chosen to develop the project on Ethereum stack using techs like Flutter for programming the front end, Golang for the backend processing, and other tools that will support all the features ie: Infura, Jetty for high speed, scaleable implementation with blockchain.

The design guidelines formulated in the paper present several settings for estimating the efficiency of DDSS. These factors are processing time, data accuracy, throughput and vulnerability measure which are all to be considered in the evaluation of the performance of DDSS. Such measures are some of the key aspects to assess the stability, speed, and reliability of a security framework, so that it is well-protected against likely data breaches and digital hazards. The paper elaborates the role of various smart contracts in automation and securing the transactions in the blockchain-based system for sharing private healthcare data in DDSS Healthcare.

The author also discusses the different aspects of design and architectural elements that will facilitate the complex needs of contemporary Healthcare Information Management. It focuses on the application of blockchain technology for the data security issues, ML methods for data analytics and mining, and NoC technology for data communication. This integration method provides a holistic approach to securing data in the analysis and management of big data. The integration outcomes are not limited to data security and performance offering, but extend to this of medical treatment services.

VI. CONCLUSIONS AND FUTURE DIRECTIONS

Summary of Key Findings

The experiment's essential findings include the method used to evaluate the DDSS and its role in benefitting the B2C society. It underlines what were these crucial parts and patterns used, Ethereum, for blockchain execution, Flutter for UI discussions, Golang for back-end services, Infura and Jetty to bind blockchain and users and so on, and so forth. This system organization reveals the highest level of craftsmanship and ensures great sonic performance, excellent reliability and ease of use. The search continues into what the future of healthcare and the physical structures housing it will need to be in order to accommodate the thorny issues of storing and managing data. The paper also focuses on blockchain, ML, and NoC integration. Thus, there model will help in collection and surveillance precision, dataset security and authenticity in the application of blockchain technology in data security and in the application of ML tool in data collection, as well as modelling. An inter-chip communication became fast and efficient in an integrated-circuit in the NoC condition as well as in a large scale and also timely. Six GBPS throughput was obtained over M/LNoC when Wireless 3.5D Mesh was used. Significantly better than 2D Standard Mesh (1.5 Gbps) and 3D Standard Mesh (2.5 Gbps). Demonstrated up to 7 tolerable link failures and 6 node failures and additionally facilitated through wireless 3.5D Mesh and ML-directed re-routing to guarantee strong IC communication during stress. Therefore, it can meet the large-volume and real-time demands of data in many modern healthcare applications. Finally, the performance of the DDSS is evaluated in terms of instruction time, data dispatch, accuracy, and vulnerability decisions. These assessments provide a detailed examination of the system performance and best of the class features, required for highly secured transactions, from customer side to business side. The assessment of the DDSS performance includes all the elements of data integrity, speed and overall performance, and can therefore be used as a complete and secure data transaction solution for health care. MBE declined by 82.4% in comparison to EDIP and 61.02% in comparison to XGBoost, indicating there was little bias. Here, denotes that the predictions are both balanced and accurate in the sense of medical data.

The response time was kept within 75% of the maximum allowable response time, indicating strong performance scalability for huge B2C transactions. Furthermore, validation and access accuracy were over 90%, even at high transaction requests.

Finally, the study presents the overall development and evaluation of the mobile application within a B2C healthcare view. It has an extensive section on the experiment formulations, factors that should be taken into account and performance assessments. This has proven to be effective at securing data and optimizing healthcare data transactions. This deep integration of blockchain and NoC technologies is expected to offer better, secure, accurate and efficient healthcare services - thus a step closer to next generation healthcare technology systems.

Theoretical and Practical Contributions

By incorporating blockchain, ML, and NoC technologies, the field study extends the existing theoretical frameworks that build upon reliable, effective, and scalable systems. This approach offers novel perspective on how these technologies have multiplier effects, and including blockchain, data tracking and management becomes a transparent and immutable process. Simultaneously, ML is strong at processing data, and NoC is good at enhancing the communication between chips. This interdisciplinary character reinforces academic discussions, as we can witness the power of the across-fertilization of several technologies for solving advanced problems in the fields of data protection and manipulation.

It was demonstrated that the study has been fruitful in practical terms and that the DDSS implementation was very successful within a business to costumer (B2C) environment, on theoretical basis. On the practical side, it demonstrates real, real-life use of the system. The application of this system to healthcare service shows an important case on how advanced tools can drive the safety process and improve the data processing efficiency and the results accuracy. That hands-on use is an example for an early version that somebody can use with a regular template or adapt to the more specialized data security needs of other industries. In addition, the paper provides empirical evidence about the system performance such as time consumption of process, throughput and data precision which would be valuable to present to other collaboration parties who have interests in establishing similar systems at the intersection between health care and technology. Therefore, it not only promotes theoretical research and application, but becomes the dominated way to improve data security in data management system.

Limitations and Research Gaps

Although integrating these three technologies offers vast technological advancements, our research project reveals certain limitations and gaps that can be worked out with further studies. Second, in high-end NoC with pipeline delay data transmission, the performance of blockchain in terms of scalability is also a challenging issue, as the increased data throughput in NoC provides more stress for blockchain protocols to ensure the immediacy and reliability of transactions with consistent performance. It’s also the question of bequeathing further tech to healthcare systems that worries people about overheads and potential bottlenecks even as they scale. The learn abilities of ML algorithms are another challenge since they need to be adjusted in accordance with the situation. For dynamic healthcare data, modifications may have to be performed periodically to maintain the correctness and effectiveness of the algorithms. Furthermore, the work has not identified the impact of such convergence on the power consumption and the lifetime daily performance of the hardware that are employed in these systems. The above-discussed deficiencies indicate the research directions for the system integration capability, the power consumption immunity to the environment, and the adaptability to different healthcare applications, respectively.

Future Enhancement Opportunities

Although the research concept has explored multiple avenues for future enhancement, discussing technological problems first and foremost is the design of more advanced blockchains that process increased amounts of data without decreasing the speed or security of the transactions in areas of intensive healthcare.

- Improving ML algorithms can facilitate adaptation and learning from dynamic data patterns, resulting in better diagnosis and personalized treatment.
- On the other hand, increasing the efficiency of energy sucking NoC architecture might lead to aware systems but it would make the systems most suitable for wide use in low-resource settings anyways, like mobile health and remote monitoring systems.
- Moreover, further research is intended to provide the application of artificial intelligence in NoC-based applications in order to apply more sophisticated decision-making processes, thus enabling more sophisticated networks that are constantly self-optimizing so as to meet challenges of a system ahead of time and afterwards. And then, if you can push the frontier to include the operability of other budding technologies like quantum computing, you can multiply the computational power several times over and, one day, you may end up revolutionizing and speeding up the data and the way it is processed and, in a transformative way, secure all of that and so much more. These upgrades not only seek to improve upon the existing architecture but also to transform the adapting dynamic nature of technology in healthcare and health beyond.

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