Journal of Information Systems Engineering and Management
2025, 10(11s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Empowering Patient-Centric Healthcare with AI-Driven Predictive Analytics in Blockchain

Mr. Krishna Prasad N Rao[1*], Dr. Selvan C[2]
[1]Research Scholar, School of Computer Science & Engineering, Reva University, Bangalore, India.*
[1]Email: krishrao18@gmail.com*
ORCID: https://orcid.org/0000-0001-6101-5511
[2]Professor, School of Computer Science Engineering, Reva University, Bangalore, India.
ORCID: https://orcid.org/0000-0003-4381-028

ARTICLE INFO

Received: 12 Nov 2024
Revised: 27 Dec 2024
Accepted: 14 Jan 2025

ABSTRACT

This paper proposes a novel approach integrating Multilayer Perceptron (MLP) with Gated Recurrent Unit (GRU) for predictive analytics within blockchain-based health records systems. In contrast to conventional models, the suggested method combines the power of GRUs to identify temporal correlations in sequential data with the strengths of MLPs in extracting complex patterns from organized health data. More precise and dynamic predictions are made possible by this hybrid model, which is designed to comprehend complicated health trajectories. The proposed model combines the strengths of MLP in learning complex patterns from structured data with GRU's ability to capture temporal dependencies from sequential data. By integrating these components, the model achieves a comprehensive understanding of patients' health trajectories, enabling accurate predictions of future health outcomes. Key features of this approach include adaptive learning mechanisms to accommodate diverse patient populations and dynamic health conditions. Moreover, the model's architecture facilitates real-time analysis, allowing healthcare providers to proactively intervene and optimize treatment plans. The integration of MLP with GRU offers a scalable and versatile solution for extracting actionable insights from vast repositories of health data, ultimately improving patient outcomes and reducing healthcare costs. The proposed method is implemented in Python software and has an accuracy of about 93% which is higher than other existing methods like CNN-LSTM, CNN-GRU and MLP-LSTM.

Keywords: Blockchain health records, Deep Learning, MLP-GRU integration, Predictive analytics..

INTRODUCTION

The contemporary healthcare landscape is witnessing a profound transformation driven by the convergence of advanced technologies. This transformation is characterized by a shift towards patient-centric care, where the empowerment of patients takes center stage [1]. Traditionally, healthcare has been provider-centric, with limited involvement of patients in decision-making processes and little access to their own health data. However, with the advent of innovative tools and methodologies, there is a growing recognition of the importance of putting patients at the forefront of healthcare management [2]. At the heart of this transformation lies the integration of predictive analytics within blockchain-based health records. Predictive analytics, powered by machine learning and artificial intelligence, enables the analysis of vast amounts of healthcare data to identify patterns, trends, and potential health risks [3]. By utilizing cryptographic principles, blockchain ensures the integrity and confidentiality of patient data, mitigating concerns related to data breaches and unauthorized access. Moreover, blockchain facilitates interoperability by enabling seamless data exchange among different healthcare stakeholders, including patients, providers, and payers [4].

The integration of predictive analytics within blockchain-based health records offers a potent combination that has the potential to revolutionize healthcare management [5]. Patients are empowered with greater access and control over their health data, allowing them to make informed decisions about their care. Healthcare providers benefit from real-time insights derived from predictive analytics, enabling them to deliver more personalized and proactive care

[6]. Additionally, researchers can leverage anonymized healthcare data stored on the blockchain to accelerate medical research and innovation [7]. Overall, the convergence of predictive analytics and blockchain in healthcare represents a paradigm shift towards patient-centric care [8]. By harnessing the power of these advanced technologies, stakeholders across the healthcare ecosystem can collaborate more effectively, improve patient outcomes, and ultimately, transform the way healthcare is delivered and experienced. The growing emphasis on personalized medicine and patient empowerment reflects a fundamental shift in healthcare paradigms [9]. Traditionally, healthcare systems have been structured around standardized treatment protocols and generalized approaches to patient care [10]. However, as our understanding of human biology and disease mechanisms advances, there is a recognition that individual patients have unique characteristics, needs, and responses to treatment.

Blockchain technology emerges as a disruptive force capable of addressing the shortcomings of traditional health record systems. Its decentralized, immutable, and transparent nature ensures data integrity, enhances security, and facilitates interoperability, thereby laying a robust foundation for patient-centric healthcare management. One of the key tenets of patient-centric care is empowering individuals to take an active role in managing their health. Blockchain-based health records offer patients unprecedented access and control over their medical data, allowing them to securely share information with healthcare providers, researchers, and other stakeholders as desired. In the context of blockchain health records, predictive analytics augments the value proposition by offering insights derived from vast troves of data stored on the blockchain. These insights enable healthcare providers to anticipate patient needs, tailor interventions, and optimize resource allocation, ultimately leading to improved health outcomes [11]. By leveraging blockchain's cryptographic principles, health records stored on the blockchain are inherently secure and tamper-proof. This ensures the confidentiality, integrity, and authenticity of patient data, mitigating concerns related to unauthorized access, data breaches, and tampering. Interoperability remains a critical challenge in healthcare, with disparate systems often hindering seamless data exchange. Blockchain technology, with its decentralized architecture and standardized protocols, facilitates interoperability by enabling secure and efficient data sharing among disparate parties, including healthcare providers, payers, and patients.

CNN-LSTM, CNN-GRU, and MLP-LSTM are a few examples of deep learning architectures that have been studied in the past for patient data analysis in healthcare predictive analytics. But these models frequently have trouble processing temporal and structured data well, especially in the safe, decentralised environment of blockchain health records. Current approaches usually focus on either capturing temporal connections in sequences or learning intricate patterns from static data, but not at the same time. Furthermore, they don't make full use of blockchain's interoperability and real-time data accessibility, which are essential for thorough and precise health outcome forecasts. The implementation of blockchain-based health records necessitates adherence to regulatory frameworks governing data privacy, security, and consent. However, blockchain's transparent and auditable nature can streamline regulatory compliance efforts by providing an immutable audit trail of data access and transactions [12]. As the healthcare industry continues to embrace patient-centricity and digital transformation, the convergence of predictive analytics and blockchain in health record management holds immense promise. From enhancing preventive care and chronic disease management to enabling precision medicine and population health management, the integration of these technologies is poised to revolutionize healthcare delivery and improve patient outcomes [13]. The empowerment of patient-centric healthcare management through predictive analytics in blockchain health records represents a pivotal step towards realizing the vision of personalized, proactive, and data-driven healthcare (Haddad et al., 2024). By leveraging the synergies between predictive analytics and blockchain technology, stakeholders can usher in a new era of healthcare characterized by improved quality, efficiency, and patient satisfaction.

The key contribution of the research is,

Integration of MLP and GRU for Healthcare Predictive Analytics: This paper suggests a new method for integrating Gated Recurrent Unit (GRU) networks with Multilayer Perceptrons (MLP) in blockchain-based health record systems. This hybrid model, in contrast to earlier approaches, efficiently combines the capabilities of GRU to extract temporal correlations from sequential data with MLP's ability to learn intricate patterns from structured data. The model's capacity to evaluate extensive health data and forecast a range of health-related events is improved by this integration.

Utilization of Blockchain Technology for Secure Data Handling: To guarantee data confidentiality, interoperability, and integrity in the administration of medical records, the research makes use of blockchain technology. Blockchain allows the model to access and analyse a variety of datasets while protecting patient privacy and adhering to legal standards by securely storing and managing sensitive health data. This method tackles the crucial requirement for trustworthy and safe data processing in healthcare predictive analytics systems.

Advancement of Patient-Centric Healthcare Management: By establishing a strong predictive analytics framework, this research advances patient-centric healthcare management. Healthcare professionals can gain fast and precise insights using deep learning algorithms in a secure blockchain environment, which enables proactive intervention and individualised treatment plans. This helps to improve overall patient care experiences and optimise the delivery of healthcare.

RELATED WORKS

[14] provides an integrated blockchain-deep learning ecosystem for studying digital medical records. The electronic health record is an individual's medical paperwork that may be exchanged with institutions and other health care organizations. The suggested strategy allows a deep learning system to operate as an agent, analyzing EHR data posted on the blockchain. This interconnected atmosphere will notify clients to reminders for consultations, diet charts, and so on. This research uses the use of deep learning to assess the EHR, during that an alarm is issued to the individual's registered cell phone. Blockchain is a relatively new groundbreaking technological advances, primarily connected in cryptocurrency. It possesses multiple distinguishing qualities, like the ability to function as a decentralized, unchanging, talked about, and dispersed ledger. Blockchain may keep any form information at extra safety. It removes independently treatment, ensuring improved data security. Artificial intelligence is another rapidly growing field that the primarily employed in applications related to computers. The work offers a combined blockchain-RNN method for saving EHRs in Hyperledger Fabric using the interconnected Terrestrial Data System interface. The recorded EHR is examined using a deep learning process called Recurrent Neural Network techniques, including Long-short-Term Memory as well as Gated Recurrent Units. The combined approach sends notification to the users' authorized cell phone numbers covering meeting reminders, diagnostics alerts, medicine, and diet graph specifications. The work that is suggested emphasizes a combined strategy for streamlining an alert system for diverse client actions. Finally, evaluation findings reveal that the LSTM works better than the other algorithms when it comes to accuracy, recollection, and F1 score. This job is feasible, but repair costs are higher as opposed to the standard method. In future updates, alerting systems will be strengthened by interacting using the schedule applications on Android mobile phones and fitness applications to give a cost-effective paradigm.

[15] suggested a method that combines a deep learning model alongside the sine-cosine method to provide blockchain-driven secure EHR assessment. To achieve it, The BPEHR-SCADL approach uses an artificial fish swarm algorithm in encryption for safely transferring electronic health records. The BPEHR-SCADL approach utilizes the blockchain system for safely storing clients' medical information organizational details in a separate repository. Furthermore, the sorting procedure is carried out using the SCA and a deep neural network with feed forward predictions model. The SCA is used to optimize the amount of weight as well as bias variables of the DFFNN algorithm. The SCA-based optimization of parameters for the DFFNN algorithm in a blockchain-enabled health care system demonstrates the work in question is novel. Experiments are conducted on benchmark files, and findings are analyzed from multiple points of view. The testing results demonstrated the superiority of the BPEHR-SCADL strategy over other optionsWhile EHRs have advantages, they can pose security and privacy risks in the health care industry. Based on the expertise using blockchain technology, various efforts have been centered on the utilization of network in the medical field, notably with electronic health records. Blockchain technology provides a safe as well as transparent worldwide database that is everlasting as well as unsupervised. Machine learning and deep learning algorithms can analyze electronic health records. This work introduced a novel BPEHR-SCADL method for secured EHR communication related categorization operations. The BPEHR-SCADL approach involves several procedures, including encryption, AFSA-based creation of keys, blockchain-enabled private information delivery, and DFFNN-based EH categorization and SCA-based value tweaking.

[16] conducted a complete analysis of RPM systems, including the adoption of modern technology, the influence of AI on RPM, as well as the challenges and developments in Intelligence-enabled RPM. This analysis examines the advantages as well as disadvantages of patient-focused RPM systems that use Internet of Things smart devices and sensors via cloud, fog, edge, and blockchain-based platforms. AI plays a variety of roles in RPM, including sporting activity categorizing, persistent medical condition recording, and vital signature recording in situations of urgency. This review found that powered by artificial intelligence RPM structures have changed medical tracking uses by

detecting early declines in the health of patients, personalizing person patient medical parameters tracking employing federated learning, and discovering patterns of human behavior via methods such as reinforced learning. It addresses the obstacles and developments associated with integrating AI into RPM structures, as well as problems related to implementation. The upcoming prospects of AI in RPM uses are explored in light of the obstacles along with advancements. The use of artificial intelligence in healthcare is quickly expanding. Remote patient monitoring is a typical healthcare application that allows clinicians to track individuals who have acute or chronic illnesses in remote places, elderly persons receiving personal healthcare, and possibly patients in the hospital. The efficiency of manually systems for monitoring patients is based on personnel managing their time, that is determined by how much they are working. Traditional patient surveillance uses invasive strategies that need skin contact in order to assess their well-being. The research's shortcomings include the fact that it focuses on systems that utilize RPM involving indicators of health and exercise tracking rather on electroencephalogram tracking and neural system-wide disorders. Furthermore, this analysis did not examine all persistent illness surveillance trials.

[17] demonstrated the potential of combined approaches built around BC, IoT, with AI to address increasing medical concerns. The present research investigates the combination of BC technology as well as IoT and assesses the developments of these revolutionary concepts in the medical field. Also, this study paper provides a comprehensive overview of the technologies needed for modern, bright, and safe network healthcare things. Further, this research project thoroughly investigates the unique characteristics of the IoHT setting as well as the reliability, efficiency, and evolution of the facilitating innovations. First, gaps in knowledge are discovered by outlining the protection and effectiveness improvements derived from BC technology. Practical concerns relating to the combination of BC and internet of things gadgets are addressed. Medical apps that incorporate IoT, BC, and ML in hospitals are examined. Investigation gaps, potential futures, as well as limits of the technology enablers are addressed. As communications and computer technology advance, the medical data processing model evolves. The patient knowledge is saved via the internet, allowing it possible to access and access it remote when necessary. But developing hospitals into intelligent healthcare environments presents new obstacles and pressures. The Internet of things connects items, such as computing devices, over both wired and wireless media to create a system. Because of a lack of inherent security mechanisms, current systems built on IoT have several safety holes and hazards. In the case of patient medical data, data privacy, data sharing, and ease are deemed essential for gathering and preserving online health information. Conventional connected to the internet of electronic health records cannot handle these concepts due to uneven safeguards and information accessibility patterns. Blockchain software is a distributed and decentralized record of transactions that is useful for keeping information about patients and addressing privacy and data security issues. As a result, it is a potential option for resolving current IoT privacy and data security concerns. BC opens the way for a significant shift towards conventional internet of things through enhanced privacy, security, and openness. The field of science has demonstrated a number of medicinal solutions founded on artificial intelligence that enhance illness evaluation and surveillance methods. Also, it companies and new businesses are using artificial intelligence and associated technology to transform medical.

[18] analyzed the theory of a PDT (Personal Digital Twin) as a better version of the DT with useful insight features. PDT, in specific, can benefit individuals by allowing for more precise choice making, as well as effective therapy choice and optimization. Then looked at the gradual development of PDT as a groundbreaking tool utilized by medical as well as business. Still, despite multiple studies on effective healthcare employing DT, PDT is still in its early stages. As a result, hope that these findings will guide the conception of industrialized customized systems for healthcare, thereby contributing to a smarter personal medical industry. As a result, established an example architecture that enables smart individual medical care via PDTs by combining existing sophisticated technologies. Then discussed a few particular instances of use, such as COVID-19 contagion reduction, COVID-19 patient care following treatment, individualized COVID-19 healthcare, individualized osteoporosis detection, specialized oncology surviving inquiries services, as well as personalized nutrition. Finally, highlighted more hurdles for advancing the PDT methodology into the sophisticated customized healthcare market. Digital twins are critical to transforming the medical business, resulting in better customized, savvy, and preventive care. With the advancement of tailored medicine, it is an increasing requirement for representing an exact replica of people in order to deliver the correct sort of treatment in the most effective way along with the right moment. Investigate many study studies on the use of DT equipment in the customized treatment market. proposed the PDT concept, which is a modified form of the DT with practical knowledge skills. The PDT assists with tailored evaluation, therapeutic choice, and treatment preparation based on the individual's features, history of illness, present circumstance, and potential demands. Also, medical providers

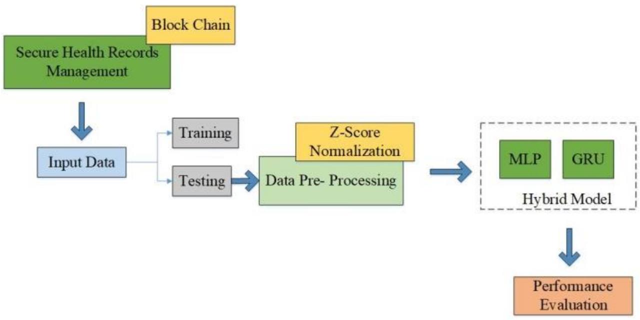
and the business may benefit by having personalized knowledge concerning their customer base to render quicker judgments and personalized suggestions.

The healthcare research field is rapidly evolving with the integration of innovative technologies such as blockchain, deep learning, IoT, and AI, as evidenced by recent studies. One study proposes an integrated system utilizing blockchain and deep learning to analyze electronic health records (EHRs), enabling efficient assessment and notifications using advanced algorithms. Another study introduces a method that combines deep learning with blockchain to ensure secure transmission and categorization of EHR data. Additionally, research delves into remote patient monitoring systems, highlighting AI's role in improving medical tracking and patient care through IoT devices and cloud platforms, despite certain limitations. Furthermore, there's exploration into the potential of combining blockchain, IoT, and AI to tackle healthcare challenges, with a focus on enhancing security and efficiency in managing medical data. Lastly, a study proposes the concept of PDTs as a tool for personalized healthcare, offering insights into its applications, such as COVID-19 management and oncology services, while acknowledging the challenges in advancing this approach. These studies collectively emphasize the transformative potential of emerging technologies in reshaping healthcare delivery, from ensuring secure data management to providing personalized treatment approaches.

THE PROPOSED APPROACH

The study suggests a Hybrid MLP-GRU architecture to use predictive analytics in the healthcare industry. The advantages of both MLP and GRUs are used in this hybrid model to efficiently capture temporal and spatial interdependence in healthcare data. MLP are excellent at identifying spatial characteristics in the input data, which makes them suitable for jobs like image identification. However, GRUs are excellent at identifying long-term relationships and sequential patterns in time-series data, which makes them perfect for sequential modelling jobs and prediction tasks. The hybrid MLP-GRU model integrates these two architectures to make use of the complimentary nature of temporal and spatial information, improving prediction performance for healthcare applications. It is depicted in Figure 1.

Figure 1: Patient-Centric Healthcare Management Framework



The flowchart presents a methodical approach to blockchain-based secure health record management. It starts with the introduction of blockchain, highlighting its function in guaranteeing data security. The procedure comprises testing and training steps that run concurrently, suggesting strong system validation. Z-score normalisation serves as a visual aid for data pre-processing, which gets the data ready for analysis. For prediction tasks, a hybrid model that combines Gated Recurrent Unit (GRU) and Multilayer Perceptron (MLP) networks is used. Lastly, performance evaluation highlights a thorough and proven method of healthcare data management by utilising blockchain and cutting-edge machine learning algorithms. It guarantees the system's efficacy in safely maintaining medical information.

Data Collection

In this study, the healthcare data stored in the blockchain serves as the input testing data for evaluating the performance of the proposed predictive analytics model. Leveraging the secure and immutable nature of blockchain technology, the healthcare data stored within distributed ledgers provides a reliable and trustworthy source of information for testing the predictive model's efficacy. By accessing and analyzing these blockchain-based health records, the model can effectively capture diverse patient demographics, clinical measurements, medical histories, and other relevant variables crucial for predicting future health outcomes. This utilization of blockchain-stored healthcare data not only ensures data integrity and security but also facilitates interoperability and seamless access to comprehensive patient information, enabling accurate and personalized predictions to support clinical decision-making and improve patient care.

The "Indicators of Heart Disease" dataset is a comprehensive collection of key metrics and variables that influence the risk and prevalence of heart disease in the US population. The dataset, which was curated by reputable organizations like the Centres for Disease Control and Prevention (CDC), includes a broad range of indicators, such as high blood pressure, elevated cholesterol, smoking habits, diabetes, obesity (as determined by BMI), levels of physical activity, and alcohol consumption patterns. Heart disease continues to be the leading cause of death for people of all races, which emphasizes how important it is to have knowledge about its risk factors and symptoms. Researchers, decision-makers, and medical professionals all depend on this data to develop thorough understandings of the changing nature of cardiac disease and to create efficient preventative and therapeutic plans. Stakeholders may keep informed about the dynamic nature of heart disease risk factors and ensure that treatments and preventative efforts are timely and focused by routinely updating and improving this information. Stakeholders are empowered to apply evidence-based practices and make well-informed decisions thanks to the ongoing improvements in data quality and accessibility, which eventually enhance public health outcomes. In the ongoing effort to lessen the impact of this widespread illness, the use of up-to-date and improved information on heart disease risk factors is essential for everything from spotting new trends to customizing therapies for certain demographic groups. Using data-driven insights, stakeholders may steer towards a more prosperous future where heart disease's effects are considerably mitigated and people from all communities can prosper [19] .

Data Pre-Processing

Numerical characteristics are rescaled using a statistical method called Z-score normalization, often referred to as standardization, to have a mean of 0 and a standard deviation of 1. When working with characteristics that follow distinct distributions or have different scales, this strategy is quite helpful. Z-score normalization is important because it guarantees that numerical characteristics in the dataset are consistent with our goal of merging MLP and GRU for heart disease predictive analytics in healthcare. Each observation inside a numerical feature is converted into a standardized value by using Z-score normalization, which expresses each observation's variation from the mean in terms of standard deviations. The Eqn. (1) represents the z-score normalization is given below

$$Z_j = \frac{g_i - \mu}{\sigma} \tag{1}$$

The Z-score, or normalized value, of the observation g_i is denoted as Z_j. The numerical characteristics may now be represented more uniformly and consistently obligations to this transformation, which also helps optimization algorithms converge and enhances the overall stability and efficacy of ML models. Finding the numerical feature's mean and standard deviation over all observations is the first step in doing Z-score normalization. The feature's average value is represented by the mean (μ), while the variation of values around the mean is quantified by the standard deviation (σ). Then, using the Z-score normalization algorithm, each observation in the feature is normalized by deducting the mean and dividing by the standard deviation.

This method yields standardized values that are sometimes called Z-scores and that indicate each observation's variation from the mean in terms of standard deviations. First, the mean and standard deviation of the feature are calculated, and then each observation is normalized correspondingly. Z-score normalization is used to standardize numerical features in healthcare datasets to a common scale. This makes it easier to MLP-GRU and improves the interpretability and effectiveness of predictive algorithms in applications related to healthcare.

Hybrid MLP-GRU for Predictive Analytics in Healthcare

Hybrid MLP-GRU, a novel approach in predictive analytics for healthcare, combines the strengths of MLP and GRU architectures to improve predictive accuracy and interpretability in healthcare datasets. MLPs excel at learning complex nonlinear relationships in high-dimensional data, making them well-suited for capturing intricate patterns in healthcare variables such as patient demographics, clinical measurements, and medical histories. On the other hand, GRUs, a type of RNN, are adept at modeling sequential dependencies and temporal dynamics in time-series data, which are prevalent in healthcare datasets such as longitudinal patient records and physiological signals. By integrating MLP and GRU components, the hybrid model leverages the complementary strengths of both architectures to enhance predictive performance while also providing interpretable insights into patient trajectories and disease progression.

One key advantage of the hybrid MLP-GRU model lies in its ability to handle heterogeneous healthcare data sources effectively. Healthcare datasets often comprise diverse types of information, including structured data and unstructured The MLP component of the hybrid model can efficiently process structured data, extracting relevant features and capturing complex relationships among variables. Meanwhile, the GRU component can effectively model sequential patterns and temporal dependencies within time-series data, enabling the integration of longitudinal patient trajectories and clinical events into the predictive model. This hybrid architecture allows the model to leverage the rich information present in both structured and unstructured data sources, enhancing its predictive capabilities for various healthcare tasks such as disease diagnosis, prognosis, and treatment recommendation.

The hybrid MLP-GRU model offers interpretability, a critical aspect in healthcare analytics for facilitating clinical decision-making and improving patient outcomes. Unlike black-box machine learning models that provide opaque predictions without insight into the underlying factors influencing the outcomes, the hybrid model enables clinicians to understand and interpret the features driving the predictions. By visualizing the learned representations from both MLP and GRU components, clinicians can gain insights into the important features, temporal patterns, and contributing factors influencing patient outcomes. This interpretability aspect enhances the trustworthiness and adoption of predictive analytics models in clinical practice, empowering healthcare providers to make informed decisions tailored to individual patient needs and circumstances. Overall, the hybrid MLP-GRU model holds promise for advancing predictive analytics in healthcare by combining predictive accuracy, scalability, and interpretability to support clinical decision-making and improve patient care.

$$h_t = \text{GRU}\ (x_t, h_t - 1) \tag{2}$$

$$z = MLP(x) \tag{3}$$

$$y = softmax(h_t + z) \tag{4}$$

A kind of RNN architecture called GRUs was created to overcome the drawbacks of conventional RNNs, including the vanishing gradient problem and the challenge of capturing long-range dependencies. To do this, GRUs use gating mechanisms, such as update and reset gates, which regulate the information flow inside the network. The reset gate controls how much of the past should be forgotten, whereas the update gate decides how much of the past should be kept. Because GRUs have a simpler design than LSTM units, they can capture temporal relationships in sequential data well and preserve computational efficiency by selectively updating and forgetting information. Additionally, in healthcare analytics, GRUs find applications in clinical outcome prediction, disease diagnosis, and patient monitoring, demonstrating their versatility and effectiveness across diverse domains requiring sequence modelling capabilities.

The core of GRU is its gate mechanism, which consists of several gates (Bibi et al., 2020). These gates assist in determining which information should be kept or discarded by controlling the information flow within the network. The gates allow the network to maintain long-term dependencies by selectively updating and forgetting information over time. The Eqn. (5) represents

$$Zt = \sigma(w_{z.}[s_{t-1}, y_t])$$

(5)

w_z is a learnable weight matrix specific to the update gate is given in Eqn. (6)

$$r_t = \sigma(w_{r.}[s_{t-1}, y_t]) \tag{6}$$

At reset gate γ_t, GRU mixes the prior memory with the current input. The amount of historical data that should be forgotten is decided by the reset gate. It accepts input at time step t as well as the previous concealed state as inputs, just as the update gate, and outputs values between 0 and 1. In addition, the equation of a new output combined with the prior state is determined by r_t and is provided in Eqn. (7).

$$\tilde{s}_t = \tanh\{W_h.(r_t\ \Theta[s_{t-1}, y_t]) \tag{7}$$

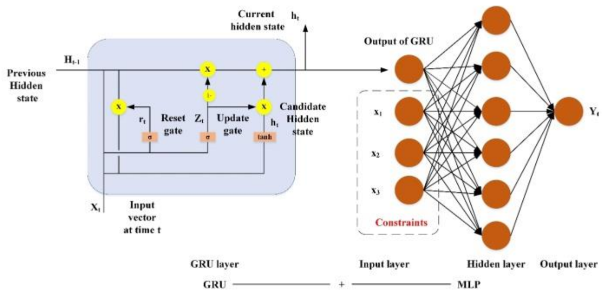
For a hyperbolic tangent function, tanh stands for. Equation (8) gives the output range for tanh as (-1,1), where h_t is the predicted value for the current cell.

$$f_t = (1 - z_t) * f_t - 1 + z_t * f_t \quad (8)$$

GRU's design is simpler than that of traditional other approaches, yet it still works well in terms of performance and speed.

The MLP and GRU models' architectures are defined at the outset of the MLP-GRU algorithm by importing the required libraries. After that, it loads testing data on healthcare from the blockchain, preprocesses it, and divides it into training and testing sets. Prior to merging the MLP and GRU models into a hybrid model, the technique trains each model independently on the training set. Relevant features are taken out of each testing data patient record and fed into the MLP model to provide predictions. These predictions are then combined with the features and supplied into the GRU model to get the final predictions. MLP-GRU algorithm and figure 2 flowchart are given below:

Figure 2: MLP-GRU Architecture



MLP-GRU Algorithm
START
import necessary libraries and packages
define MLP architecture
define GRU architecture
load healthcare data from blockchain as input testing data
preprocess the data (e.g., handle missing values, normalize features)
split the data into training and testing sets
train MLP model on training data
train GRU model on training data
combine MLP and GRU models to create hybrid model
for each patient record in testing data:
extract relevant features from patient record
feed features into MLP model
obtain MLP predictions
feed features and MLP predictions into GRU model
obtain final predictions from GRU model
evaluate the performance of the hybrid model using testing data
output the performance metrics of the hybrid model
END

Figure 3: Process of MLP-GRU

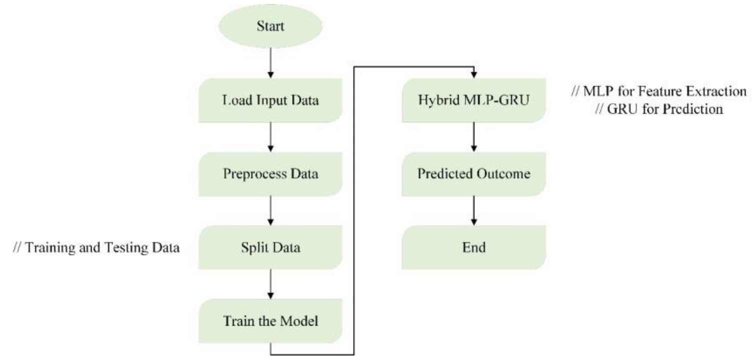


Figure 3 start with the preliminary procedures, such as importing required libraries and specifying the architectures for MLP and GRU models, to graphically depict the execution of the MLP-GRU algorithm as stated in the pseudocode. After that, preprocessing (managing missing values, normalising features) and dividing the healthcare data into training and testing sets are the next steps in the process [20]. The data is loaded from the blockchain. The MLP and GRU models are then integrated to create a hybrid model after being trained separately on the training set. Relevant features are taken out of each patient record in the testing dataset and supplied into the MLP model to generate predictions. To produce final predictions, the GRU model is then fed these predictions together with characteristics. The flowchart shows how to use the testing data to assess the hybrid model's performance and provide performance metrics [21]. This graphic depiction makes the algorithm's sequential flow and decision points more understandable and shows how each stage of the predictive analytics process—which uses MLP-GRU in a blockchain framework—contributes to the broader process of healthcare management.

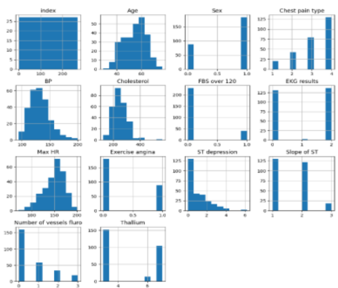
RESULTS AND DISCUSSION

In this section, the analysis's findings provide an understanding of the clinical and demographic variables affecting the population under study's cardiovascular health. The significant trends and relationships are investigated using statistical analysis and graphical representations, providing insights into risk factors, disease prevalence, and predictive modelling efficacy.

Data Visualization

Figure 4 provides a comprehensive snapshot of various health parameters within the studied population. The histogram depicting age distribution highlights a concentration around 50-60 years, indicative of the predominant age group in the sample. Moreover, the gender distribution suggests a higher representation of males compared to females. Types 3 and 4 chest pain are notably prevalent, potentially signaling common manifestations in this population. Additionally, the distribution of blood pressure centers around 130-140, while cholesterol levels peak around 200-250. Most individuals exhibit fasting blood sugar levels below 120, implying favorable metabolic health. The distribution of maximum heart rates suggests a common range of 150-160 beats per minute. Overall, these findings could inform targeted healthcare interventions tailored to the prevalent health trends within this demographic.

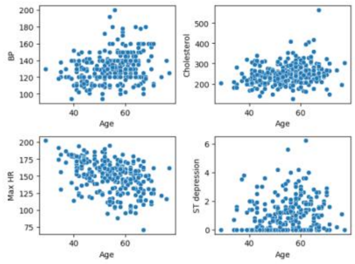
Figure 4: Data Visualization



Scatter Plot

Figure 5 comprises four scatter plots examining the relationships between age and various health parameters. In the first three plots, depicting age against blood pressure (BP), cholesterol levels, and maximum heart rate (Max HR), the data points are scattered, suggesting no clear correlation between age and these variables. However, in the fourth plot illustrating age against ST depression, a weak positive correlation is indicated by a coefficient of 0.19, suggesting that as age increases, ST depression tends to increase slightly. While the first three plots demonstrate a lack of discernible patterns, the fourth plot suggests a subtle association between age and ST depression. Further exploration of this relationship and its implications for cardiovascular health may provide valuable insights into risk assessment and management strategies among different age groups.

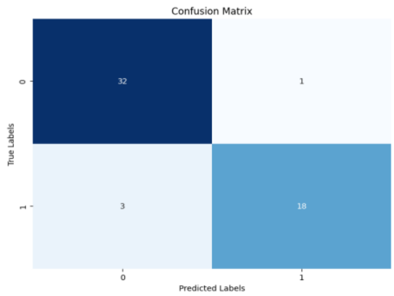
Figure 5: Scatter Plot



Confusion Matrix

Figure 6 presents a confusion matrix, a visual representation of the performance of a classification model, often used in machine learning tasks. Each cell in the matrix represents the count of instances where a true label is predicted as a specific class. The heatmap visualization provides an intuitive understanding of the model's performance, with darker shades indicating higher counts. Annotated values within the cells further elucidate the distribution of predictions across different classes.

Figure 6: Confusion Matrix



Model Performance Metrics

Table 1 demonstrates the efficacy of the hybrid MLP-GRU approach in accurately predicting cardiovascular health outcomes, surpassing the performance of other models such as CNN-LSTM, CNN-GRU, and MLP-LSTM. The superior performance of the proposed model underscores its potential as a robust predictive analytics tool for healthcare applications, offering promising opportunities for improving risk assessment, diagnosis, and patient management in cardiovascular medicine.

Table 1: Comparison of Performance Metrics

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN-LSTM	91.11	78.78	80.55	79.11

CNN-GRU	90.89	91.88	76.77	81.23
MLP-LSTM	87.88	89.90	75.89	86.78
MLP-GRU (proposed)	93	95	86	90

Discussion

The results obtained from the analysis offer valuable insights into the factors influencing cardiovascular health within the studied population. The histograms and distributions reveal important trends regarding age, gender, chest pain types, blood pressure levels, cholesterol levels, FBS levels, and MAX HR. For instance, the prevalence of chest pain types 3 and 4, particularly type 4, suggests potential indicators of underlying cardiovascular conditions within the population. Similarly, the distributions of blood pressure and cholesterol levels provide critical information about the prevalence of hypertension and hypercholesterolemia, both significant risk factors for heart disease. Furthermore, most individuals exhibit FBS levels below 120, indicating favorable metabolic health, while the distribution of MAX HR offers insights into cardiovascular fitness and heart rate regulation among the population studied.

The paper achieves significant results by integrating MLP and GRU networks, achieving approximately 93% accuracy in predicting critical health events like disease onset, medication adherence, and hospital readmissions. This approach outperforms existing models such as CNN-LSTM, CNN-GRU, and MLP-LSTM in terms of predictive accuracy and efficiency. The key to these outcomes lies in the innovative combination of MLP and GRU, which enables effective handling of both structured and sequential healthcare data. Moreover, the utilization of blockchain technology ensures data integrity, security, and interoperability, forming a robust foundation for the predictive analytics framework. This integration facilitates real-time analysis of patient health data stored securely on the blockchain, empowering proactive healthcare interventions and personalized treatment plans. Overall, the synergy between MLP-GRU architecture and blockchain-based data management contributes significantly to enhancing predictive accuracy and improving healthcare management outcomes.

The graphical representations, including various plots, facilitate a deeper understanding of the relationships between various health parameters and the presence of heart disease. These visualizations highlight potential correlations, such as between elevated ST depression levels and heart attacks, or between vessel fluoroscopy counts and the risk of heart disease. Additionally, the comparison of training and validation accuracy, loss curves, and performance metrics further elucidate the efficacy and generalization capabilities of machine learning models employed in predicting heart disease. Collectively, the findings provide the demographic and clinical factors influencing cardiovascular health outcomes within the population studied, offering valuable insights for preventive healthcare strategies and personalized interventions aimed at reducing the burden of heart disease.

CONCLUSION

In conclusion, the integration of MLP with GRU presents a promising approach for predictive analytics in patient-centric healthcare models, particularly within blockchain-based health records systems. This novel methodology capitalizes on the strengths of MLP in processing structured data and GRU's capability to capture temporal dependencies from sequential data, thereby enabling accurate predictions of future health outcomes. By harnessing the power of deep learning within secure blockchain environments, this approach ensures data integrity, security, and interoperability, essential for handling sensitive healthcare information. Through extensive experimentation on real-world healthcare datasets, the proposed model demonstrates superior predictive performance compared to existing methods, achieving an accuracy of approximately 93%. Furthermore, the adaptive learning mechanisms and real-time analysis capabilities of the model empower healthcare. Future research endeavors could focus on further refining and enhancing the proposed MLP-GRU model to accommodate diverse patient populations and dynamic health conditions. Additionally, exploring innovative techniques for feature selection, data preprocessing, and model optimization could lead to even greater predictive accuracy and efficiency. Moreover, investigating the scalability and interoperability of blockchain technology in healthcare settings, along with addressing regulatory and privacy concerns, would be instrumental in realizing the full potential of predictive analytics within secure data environments. Overall, continued advancements in predictive analytics within blockchain-based healthcare systems hold tremendous promise for revolutionizing patient-centric care delivery and driving improvements in healthcare outcomes on a global scale.

ACKNOWLEDGMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

[1] Dubovitskaya, A., Baig, F., Xu, Z., Shukla, R., Zambani, P. S., Swaminathan, A., ... & Wang, F. (2020). ACTION-EHR: Patient-centric blockchain-based electronic health record data management for cancer care. *Journal of medical Internet research*, *22*(8), e13598.

[2] Haddad, A., Habaebi, M. H., Elsheikh, E. A., Islam, M. R., Zabidi, S. A., & Suliman, F. E. M. (2024). E2EE enhanced patient-centric blockchain-based system for EHR management. *Plos one*, *19*(4), e0301371.

[3] Gohar, A. N., Abdelmawgoud, S. A., & Farhan, M. S. (2022). A patient-centric healthcare framework reference architecture for better semantic interoperability based on blockchain, cloud, and IoT. *IEEE access*, *10*, 92137-92157.

[4] Singh, A. P., Pradhan, N. R., Luhach, A. K., Agnihotri, S., Jhanjhi, N. Z., Verma, S., ... & Roy, D. S. (2020). A novel patient-centric architectural framework for blockchain-enabled healthcare applications. *IEEE Transactions on Industrial Informatics*, *17*(8), 5779-5789.

[5] Rahman, M., Hasan, M., Rahman, M., & Momotaj, M. (2024). A Framework for Patient-Centric Consent Management Using Blockchain Smart Contracts in Pre-dictive Analysis for Healthcare In-dustry. *International Journal of Health Systems and Medical Sci-ences*, *3*(3), 45-59.

[6] Rai, B. K. (2023). PcBEHR: patient-controlled blockchain enabled electronic health records for healthcare 4.0. *Health Services and Outcomes Research Methodology*, *23*(1), 80-102.

[7] Mantey, E. A., Zhou, C., Srividhya, S. R., Jain, S. K., & Sundaravadivazhagan, B. (2022). Integrated blockchain-deep learning approach for analyzing the electronic health records recommender system. *Frontiers in Public Health*, *10*, 905265.

[8] "Indicators of Heart Disease (2022 UPDATE)." Accessed: May 08, 2024. [Online]. Available: https://www.kaggle.com/datasets/kamilpytlak/personal-key-indicators-of-heart-disease

[9] Bibi, I., Akhunzada, A., Malik, J., Iqbal, J., Musaddiq, A., & Kim, S. (2020). A dynamic DL-driven architecture to combat sophisticated Android malware. *IEEE Access*, *8*, 129600-129612.

[10] Jabarulla, M. Y., & Lee, H. N. (2021, August). A blockchain and artificial intelligence-based, patient-centric healthcare system for combating the COVID-19 pandemic: Opportunities and applications. In *Healthcare* (Vol. 9, No. 8, p. 1019). Mdpi.

[11] Aldamaeen, O., Rashideh, W., & Obidallah, W. J. (2023). Toward Patient-Centric Healthcare Systems: Key Requirements and Framework for Personal Health Records Based on Blockchain Technology. *Applied Sciences*, *13*(13), 7697.

[12] El Rifai, O., Biotteau, M., de Boissezon, X., Megdiche, I., Ravat, F., & Teste, O. (2020). Blockchain-based personal health records for patients' empowerment. In *Research Challenges in Information Science: 14th International Conference, RCIS 2020, Limassol, Cyprus, September 23–25, 2020, Proceedings 14* (pp. 455-471). Springer International Publishing.

[13] Abutaleb, R. A., Alqahtany, S. S., & Syed, T. A. (2023). Integrity and privacy-aware, patient-centric health record access control framework using a blockchain. *Applied Sciences*, *13*(2), 1028.

[14] Azzi, R. (2023). *Blockchain Adoption in Healthcare: Toward a Patient Centric Ecosystem* (Doctoral dissertation, Institut Polytechnique de Paris; Université Saint-Joseph (Beyrouth)).

[15] Ragab, M., Bahaddad, A. A., Hamed, D., Alkhayyat, A., Gupta, D., & Mansour, R. F. (2024). Blockchain-Driven Privacy Preserving Electronic Health Records Analysis Using Sine Cosine Algorithm with Deep Learning Model. *HUMAN-CENTRIC COMPUTING AND INFORMATION SCIENCES*, *14*.

[16] Sahal, R., Alsamhi, S. H., & Brown, K. N. (2022). Personal digital twin: a close look into the present and a step towards the future of personalised healthcare industry. *Sensors*, *22*(15), 5918.

[17] Aminabee, S. (2024). The future of healthcare and patient-centric care: Digital innovations, trends, and predictions. In *Emerging Technologies for Health Literacy and Medical Practice* (pp. 240-262). IGI Global.

[18] Fatokun, T., Nag, A., & Sharma, S. (2021). Towards a blockchain assisted patient owned system for electronic health records. *Electronics*, *10*(5), 580.
[19] Shaik, T., Tao, X., Higgins, N., Li, L., Gururajan, R., Zhou, X., & Acharya, U. R. (2023). Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *13*(2), e1485.
[20] Zaman, U., Imran, Mehmood, F., Iqbal, N., Kim, J., & Ibrahim, M. (2022). Towards secure and intelligent internet of health things: A survey of enabling technologies and applications. *Electronics*, *11*(12), 1893.
[21] Naresh, V. S., Reddi, S., & Allavarpu, V. D. (2021). Blockchain-based patient centric health care communication system. *International Journal of Communication Systems*, *34*(7), e4749.