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RESEARCH ARTICLE

Big Data Analytics Model Using Artificial Intelligence (AI) and 6G Technologies for Healthcare

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ABSTRACT Artificial Intelligence (AI) and 6G technologies promise to revolutionize the healthcare domain by enhancing the accuracy and diagnosis the patient monitoring in a real-time environment. The integration of AI and 6G technologies holds substantial promise for transforming healthcare systems. AI's capabilities in complex data analysis, combined with the high speed and reliable 6G networks significantly improve the healthcare domain. However, the integration and application aspects of both technologies are still evolving. Thus, to fill this gap. Herein, we propose an advanced big data analytics model. Our proposed model has several phases, for instance, data collection, data selection and preprocessing, and analytical phase. Each phase has different functions applied to the preprocessed data and finally, the results are shown to the user. We have carried out several experiments and the network performance and efficiency are measured in terms of latency throughput and reliability (in terms of error rate). The achieved experimental result validate that the proposed model processed a large amount of data in a very short time. The reliability of the proposed model is better than earlier models and the execution time is efficient and also applicable in healthcare.

INDEX TERMS Big data, artificial intelligence, 6G technology, telemedicine.

I. INTRODUCTION

Artificial Intelligence (AI) and the 6G wireless networks are anticipated to serve as the key to the future paradigm change in the healthcare industry [1]. This forefront segment provides an overview of how the advent of these modern technologies is preparing the healthcare system for tailoring the provision of health services, diagnosis, therapy & monitoring of patients. The healthcare sector is the largest industry in the developing world, experiencing an existential change due to fast-paced technological advancement [2]. AI used to be somewhat alien to the medical profession. Still, its role is suddenly becoming decisive as AI opens new horizons in clinical data analysis, diagnostics, and individual treatment personalization [3].

AI systems, while they deal with a huge amount of therapeutic data, can give us their thought and decisions that are beyond human capability [4]. Machine learning algorithms excel at performing image analysis, often surpassing human experts in efficiency, which drives early disease diagnosis and improves patient outcomes [5].

To support the vast data demands of these AI-driven applications, next-generation 6G networks offer ultra-fast internet connections with minimal delay and high data handling capacity. These features are undoubtedly only some of the critical ones for AI in healthcare to succeed. The

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key features of 6G, like low latency and high reliability, are even more critical for applications such as remote surgery and real-time monitoring of patients because, in such applications, only milliseconds matter. The increasing internet connectivity supported by 6G also creates conditions for the broad spread of Internet Of Medical Things (IoMTs) utilization whereby patients can be monitored continuously and data collected [6]. AI, along with 6G in the health sector, is anticipated to foster precision, efficacy, and access to healthcare at a rapidly progressing rate. Such integration allows telemedicine, distant diagnostics, and deploying AI-powered predictive models for preventive healthcare. Furthermore, the system is expected to enhance health provisioning services in remote and under-serviced areas where access to professional medical staff is limited primarily [7], [8].

The introduction of AI with 6G technology is one of the key elements of Healthcare 4.0 [9]. This integration will mark a remarkable transition in the healthcare delivery system as the input capacity of smart healthcare systems is increased. The capability of AI to quickly process data reliably and efficiently combined with high-speed and low-latency data transmission 6G will provide a robust platform for sophisticated healthcare applications [10]. This fusion will ensure that advances in patient care, such as real-time diagnosis, precision medicine, and early intervention, will be realized. It is through the use of AI algorithms that we can analyze complex medical data, guiding the development of personalized treatment plans [11]. Data aggregation and real-time data transmission of 6G will enable doctors and health professionals to make the right decisions in a short time, an essential feature in emergency medicine [12]. On the other hand, 6G enables the spread of wide-area telemedicine applications, guaranteeing sophisticated treatment is possible wherever health care is rendered. While 6G technology has the potential to significantly enhance digital health solutions, its current deployment in underprivileged areas is limited [13]. As infrastructure evolves, 6G could help address healthcare needs in these regions by providing the necessary bandwidth and robustness to support the Internet of Medical Things (IoMT). This includes wearable healthcare monitors and connected medical devices, which can operate continuously to collect health data in real-time, offering healthcare providers deeper insights into individual patients. This network of devices can work non-stop and collect health data on the go, which gives healthcare providers a better understanding of individual patients. Through such comprehensive monitoring of the health status, there appears the probability of early diagnosis of health problems, preventive medical care, and accurate treatment programs [14].

AI and 6G, alongside modern-day technology, have been introduced into healthcare to enhance and innovate the concept of a greater connected and responsive healthcare device. The integration allows the sharing of statistics among distinct healthcare providers and vendors, enhancing the performance, velocity, and pleasantness of basic care. By permitting real-time facts sharing and analysis, those technologies promote a more strategic approach to patient care, focusing on preventive interventions and individualized remedy plans for the needs of all.

The objective of this study is to provide a comprehensive evaluation of AI and 6G technology, helping healthcare experts, policymakers, and policymakers apprehend their effects and establish guidelines and procedures. We suggest a method that makes use of the convergence of AI and subsequent-generation generation for an extra efficient and focused affected person care machine.

The proposed big data analytics model leverages the synergistic capabilities of AI and 6G technologies to improve healthcare systems. The proposed model has several phases, i.e., data collection, data selection and preprocessing, and analysis phase. Each phase has different functions applied to the preprocessed data and finally, the results are shown to the user.

The contributions of this research are: First, we developed an advanced model of big data analysis. The proposed model analyzes big data with a massive dataset. In this example, we have shown how AI and 6G technologies can be used effectively for in-depth analysis of healthcare data and improve diagnostic accuracy and patient care. Second, we implemented the proposed model and analyzed the results of 6G technology for healthcare, mainly its capability to deliver very rapid facts and actual-time communique, which is beneficial for programs including telephony surgical procedures and far-off affected person tracking. Finally, we furnished a complete assessment of ways the mixing of AI and 6G can deal with current barriers in healthcare transport, specifically in far-off and underserved regions, thereby paving the way for extra available and green healthcare offerings. Our proposed holistic model underscores the transformative capability of integrating AI and 6G and units as a foundational framework for future research and improvement in Smart Healthcare 4.0.

The key benefits of our research are:

- The proposed model is used to identify various healthcare applications and investigate the specific applications where artificial intelligence and seamless integration of 6G can make a huge difference, such as telemedicine, remote monitoring, and emergency response systems.
- We created a roadmap and model for the effective use of AI and 6G in healthcare management that can be applied to large systems, be secure, and give access to the public.

The paper follows a structure with several key subheadings allowing for an all-over interference of AI and 6G technologies in Smart Healthcare 4.0. An introduction opens the essay by stating the intentions of integration. The related works section scrutinizes existing literature and focuses on progressions and uncovered areas of the area. These methodologies cover the analytical process as well as data simulations. The results and discussion include the findings and their negations and then follow the AI that analyzed Medical Information

TABLE 1. Summary of advancements in AI applications in healthcare.

Ref.	Focus Area	Key Findings	Significance in Healthcare AI
[15]	Pneumonia Detection using AI	Developed an AI model, CheXNet, that achieved radiologist-level accuracy in detecting pneumonia from chest X-rays.	Demonstrated the potential of AI in accurately diagnosing diseases, surpassing human performance in specific tasks.
[18]	Predictive Analytics in Healthcare	Explored various models for predicting hospital readmissions, emphasizing the role of AI in forecasting patient outcomes.	Highlighted the importance of AI in early intervention and proactive patient care through predictive analytics.
[19]	Personalized Medicine	Investigated deep learning applications for predicting drug properties and repurposing, using transcriptomic data.	Showed how AI can contribute to personalized medicine by tailoring treatments to individual genetic profiles.
[20]	AI in Robotic Surgery	Surveyed the role of machine learning techniques in enhancing surgical robotics beyond traditional instrumentation.	Illustrated the use of AI for improved precision and control in surgical procedures, enhancing patient outcomes.

Mart for Intensive Care (MIMIC) data for specific analysis insights. The paper summarizes its contributions, limitations, and suggestions for future research, ensuring that the author has improved the research on the topic.

II. RELATED WORK

A review of the current literature suggests that medical care systems are evolving in response to the era of Artificial Intelligence and 6G technologies. Such research demonstrates the multifaceted nature of the situation, which has its bright sides and challenges. In this connection, the technological, ethical, and interoperability aspects of the problem should not be underestimated.

A. ADVANCES IN AI FOR HEALTHCARE

Healthcare has witnessed significant progress in incorporating Artificial Intelligence (AI). AI technologies have played a significant role in different aspects of healthcare, such as patient diagnosis and selection of treatment plans. It still has a significant contribution to the development of the medical sector. One of the crucial domains where AI has been most applied is diagnostic processes. A machine-learning algorithm, a branch of AI, has shown promise in deciphering complicated medical information, especially diagnostic radiological images. For instance, AI systems have shown great accuracy in diagnosing diseases such as clinical images, sometimes even outperforming human doctors in some cases [15]. With this advancement, diagnosis is faster, and being accurate improves health outcomes. One of the most notable aspects of AI in healthcare is predictive analysis [16]. At present, AI-based models are widely deployed to predict patient outcomes, enabling early intervention [17]. These models utilize past medical history as well as patients' real-time vital sign data to predict the likelihood of medical events such as heart failure and infections [18]. AI has also brought a more personalized solution. AI can analyze large datasets, including genetic information, and suggest individualized treatment plans based on genetic data and other factors such as individuals' lifestyles or diseases. This strategy is entirely different from the conventional one-size-fits-all model, and this is the secret of [19]. Moreover, AI is extensively applied to robotic surgery, allowing for improved precision and control during the operation. AI robotic systems provide support during complex operations performed by surgeons by increasing their precision and reducing the need for invasive procedures [20]. AI adoption in health care has challenges, such as data privacy problems and the need for huge data sets to train AI models. Nevertheless, AI's growing capabilities and possible benefits in healthcare are inarguable and signify a severe step in medical science and patient care.

Table 1 concludes the central research on AI in health care with breakthroughs such as CheXNet for diagnosing pneumonia, predictive analytics of patients' outcomes, personalized medicine due to transcriptomics, and robotic surgery (see TABLE 1). AI capability is shown in each study to enhance diagnostics quality, forecast patient courses, tailor treatment, and permit surgery, to be precise, which may be the most significant step towards efficient, specific, and proactive health care.

B. DEVELOPMENT OF 6G NETWORK TECHNOLOGIE

The appearance of 6G network technology creates a turning point in developing wireless communications and is significantly beyond current 5G networks [21]. Once 6G takes the spot, it will be ready to serve as a basis for the most complex healthcare systems. Beyond what could be done by 5G, previous development, 6G networks are expected [22] to fully deliver transactions at dramatically increased data speeds, reduced latency, and enhanced reliability that could reach data transmission rates of up to 1 Tbps, which is nearly 100 times faster than 5G. This spike in data transmission capability enables the implementation of services that depend on real-time data processing and delivery, such as telerehabilitation and real-time medical data analysis [23]. Moreover,

TABLE 2. Key developments in 6G network.

Ref.	Key Focus Area of 6G	Main Findings	Relevance to Healthcare
[23]	Enhanced Data Rates and Latency	Foresees 6G delivering speeds of up to 1 Tbps, markedly surpassing 5G, complemented by ultra-low latency.	Crucial for immediate healthcare applications such as remote surgery and medical data analysis.
[24]	6G in Healthcare	Examines how 6G will elevate healthcare delivery by enhancing connectivity and leveraging the Internet of Everything (IoE).	Enables smooth information flow among medical devices and healthcare systems.
[25]	AI Integration in 6G	Emphasizes the merger of AI and 6G to foster intelligent and adaptable networking solutions.	Aids in the deployment of AI-powered tools for diagnostics and patient monitoring in healthcare.
[26]	Challenges and Future of 6G	Tackles the technological hurdles and underscores the necessity for novel infrastructure in the development of 6G.	Highlights concerns related to privacy and security, particularly for medical data within 6G networks.

6G intends to enforce the Internet of Everything (IoE) concept, which is meant to be the Internet of Things (IoT) and a much broader one that includes everything from individuals to objects and processes. On the other hand, a significant connectedness will be exhibited through the IoT platform, enabling efficient communication among healthcare equipment, healthcare providers, and patients as it could improve the quality and efficiency of care provision [24]. A significant characteristic of 6G networks is their deep AI-based integration, which will likely bring about intelligent networking and services that will be more adaptive, resource-efficient, and responsive to user needs. When it comes to healthcare, this fusion will take place in both diagnostics powered by AI, patient monitoring systems, and custom medical treatments [25]. The achievability of the 6G vision involves a diverse set of obstacles ranging from technological difficulties like the need to increase the perception speed and area to the construction of new infrastructure and a new standard creation procedure. Privacy and security have brought up much worry, especially concerning sensitive health information [26]. TABLE 2 shows the key developments in key technologies.

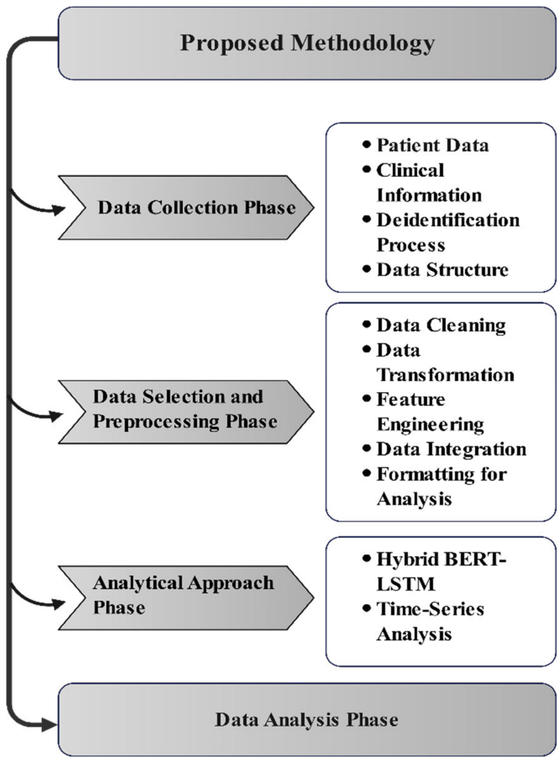

FIGURE 1. Proposed model.

III. PROPOSED MODEL

In this section, we present a proposed structured model that integrates the power of AI and 6G networks. This research aimed to assess the effectiveness of combined technologies by utilizing holistic data analysis from the real world to simulate scenarios.

The proposed model gathers, analyzes, and interprets, as depicted in Figure 1.

A. DATA COLLECTION PHASE

We have used the MIMIC dataset. This dataset is publicly available and contains unidentifiable medical information for over forty thousand patients who were admitted into critical care units at Beth Israel Deaconess Medical Center located in Boston, Massachusetts [27]. The MIMIC dataset contains demography-related details like patient age, sex, etc., and details on vital signs, laboratory test results, and drugs administered. The diverse information led to unique possibilities for applying AI models and visualizing the effect of 6G technology on healthcare facilities. The MIMIC is a useful dataset for this study; it contains all the data needed for analysis. The MIMIC-III database, the known most used iteration of this dataset, contains detailed clinical data from over 40,000 patients in the intensive care units of the Beth Israel Deaconess Medical Center in Boston, Massachusetts. This data spans from 2001 to 2012. The dataset is structured as a relational database with 26 tables, linking various types of patient information.

TABLE 3 illustrates the classification and handling of data within AI-driven healthcare systems, highlighting patient and

TABLE 3. Data types and processes in AI-enabled healthcare systems.

Data Category	Description
Patient Data	Consists of demographic details and mortality information (both in-hospital and out-of-hospital), derived from records such as the Social Security Administration Death Master File.
Clinical Information	Encompasses a wide range of medical records, including lab test results (for example, hematology, chemistry, microbiology), discharge summaries, reports from electrocardiograms and imaging studies, along with billing codes such as ICD-9.
Deidentification Process	Implemented to adhere to HIPAA regulations, this process involves the exclusion of all eighteen HIPAA-specific identifiers, such as names and exact dates, to protect patient privacy. For patients older than 89, birth dates are altered to ensure anonymity.
Data Structure	Organized into various tables, including those for recorded events (like lab tests and physiological measurements), dictionaries for terminologies and definitions, and patient care data, interconnected through identifiers (e.g., SUBJECT_ID for individuals, HADM_ID for hospital admissions).

clinical information, deidentification practices for privacy compliance, and the structured organization of data. This dataset is perfect for AI algorithms and 6G network replication in the healthcare sector because of its wide range of applications, it offers a variety of tests, from demonstration models to patient outcome studies, that allow one to understand what AI and 6G are capable of to be what in health.

B. DATA SELECTION AND PREPROCESSING PHASE

The steps for data selection and preprocessing are critical in any data-driven research, especially when using a complex and massive dataset like MIMIC. These steps ensure that the data is relevant for analysis and thus can significantly affect the results and insights obtained from the research.

This study examined missing data patterns to classify them as Missing Completely at Random (MCAR), Missing at Random (MAR), or Missing Not at Random (MNAR).

For MCAR, the probability of missing data is independent of both observed and unobserved values.

$$P(R = 1 \mid X, Y) = P(R = 1) \tag{1}$$

We used Little's MCAR test to determine if missingness was random by comparing observed patterns with expected patterns under MCAR. A non-significant p-value (typically $0.05p > 0.05$) suggests data are MCAR.

For MAR, the probability of missing data depends on the observed data but not the unobserved data:

$$P(R = 1 \mid X, Y) = P(R = 1 \mid X) \tag{2}$$

We applied logistic regression, where the missingness indicator R is modeled as:

$$R_i = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ij} + \epsilon_i \tag{3}$$

Significant predictors β_j suggest MAR.

For MNAR, the probability of missing data depends on the unobserved data itself:

$$P(R = 1 \mid X, Y) = P(R = 1 \mid Y) \tag{4}$$

We inferred MNAR by comparing the distributions of observed and missing data and conducting sensitivity analyses to see if assumptions about missing values affected the results.

The first action is to pick up specific data from the MIMIC database. Store that relatively comprehensive dataset within the research objectives that fits specific settings. Consequently, subjects should have information about such characteristics as age, sex, current diagnoses, history of hospital admissions or use of medical services, type of medications they are currently taking, or whether they received any therapy (e.g., radiation). The essence of the process is to apply some norms to the exact data selection when specific subgroups from the database are given. The next stage after selecting relevant data is the pre-processing phase, which consists of various steps.

TABLE 4 illustrates AI-based health systems' crucial data preparation stages: scrubbing, transformation, feature engineering, data integration, and preparation processes. Preprocessing is a delicate process that significantly affects the reliability and validity of the research results. It demands meticulous planning and execution to maintain honestness in the information and make it representative of intended analytical techniques.

C. ANALYTICAL APPROACH

This study utilizes several machine learning algorithms, each selected based on the type of data and the analytical objectives at hand. We used logistic regression for binary outcomes, such as predicting the probability of a patient developing a specific complication [28]. One of the primary connections between our model and the analytical approach is logistic regression, specifically applied to predict binary outcomes. Predicting whether a patient might develop a specific complication. This prediction is crucial for enabling preemptive medical interventions and improving patient care. The model was fitted using the formula:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n)}} \tag{5}$$

TABLE 4. Key steps in data preparation for AI-enabled healthcare analysis.

Step	Description
Cleaning	Involves dealing with missing values as either imputation (filling up empty values with statistical estimates) or deletion, upon the nature and magnitude of the missing data. Outliers, or those with a notably big gap, are either removed or converted.
Transformation	Data may require normalization, standardization, or other adjustments for consistent results —such as standardizing to the range between 0 and 1, with mean 0 and standard deviation 1, etc.
Feature Engineering	Developing new features or modifying existing ones can make the model more effective. For example, calculating the length of hospital stay by considering the dates of patient admissions and discharges can be useful for analysis.
Data Integration	Since the MIMIC database is built from multiple tables, each is joined using common keys, such as patient ID or admission ID, to form a unified dataset.
Formatting for Analysis	The information is organized to be usable with AI algorithms or 6G network simulations. This could include restructuring data into arrays or matrices, encoding categorical variables, or applying time-series formatting according to the analytical tools' specific needs.

Here, $P(Y = 1)$ is the probability of the event occurring, β_0 is the intercept, $\beta_1, \ldots, \beta_n$ are the coefficients for each predictor variable $X_1, \ldots, X_n$. For multiple non-linear relationships, we used the random forest classifier. This technique builds multiple decision trees in the learning process and provides the mode of the categories for classification tasks. It is essential for the management of massive data sets with large dimensionality. In a Random Forest model, for a given set of decision trees $\{T_1, T_2, \ldots, T\}$, the prediction for a classification problem is made by taking a vote of all the individual trees. For a given input X, the Random Forest prediction $\hat{Y}$ can be represented as:

$$\hat{Y} = mode\{T_1(X), T_2(X), \ldots, T_n(X)\} \tag{6}$$

This means that for each input, every tree in the forest has the chance to give a prediction ($T(X)$), and the class with the most votes among all trees wins the contest. By the way, the Random Forest algorithm uses the ensemble learning method to catch complex, non-linear relationships and, therefore, significantly improves prediction accuracy and robustness compared to single decision trees, especially those working with problems that feature a huge number of data and large dimensionality. We use neural network-based models to take advantage of the potential of deep learning, especially for unstructured data such as text from notes. Herein, we employed CNN models for the imaging data analysis that the dataset provided. They are incredibly gifted in highlighting relevant details, including spatial features like medical images. Sequentially, for the case of time-series vitals or patient records, we used RNNs since these models are suitable for handling data sequences and, hence, can effectively capture the dynamic temporal nature of such data.

1) HYBRID BERT-LSTM

Given the vast amount of unstructured text data, NLP techniques were employed to extract relevant information from textual datasets. We utilized a hybrid model combining BERT (Bidirectional Encoder Representations from Transformers) and LSTM (Long Short-Term Memory) networks for tasks such as sarcasm detection. The generation of embedded vectors is accomplished through training the BERT model, which is subsequently used as input for the following LSTM networks.

Algorithm 1 BERT-LSTM for Sarcasm Detection

Input: Textual Dataset
Output: Sarcastic or Non-Sarcastic Text
For each text t_i **do**
  Refined text $R_t^1 \leftarrow$ SpellChecker (t_i)
  Refined text $R_t^2 \leftarrow$ SpecialCharRemoval (R_t^1)
  Ready to use text $R_u \leftarrow$ Padding (R_t^2)
End For
For each text t_i **do**
  BERT encoder (B_e) $\leftarrow$ BERT-based-multilingual-uncased-model (R_u)
  Extracted features (F_e) $\leftarrow$ LSTM (B_e)
  Output (O) $\leftarrow$ Dense (F_e)
  Probability (P_S and P_{NS}) $\leftarrow$ Sigmoid (O)
  If $P_S \geq 0.5$ **then**
    Sarcastic text
  Else
    Non-Sarcastic text
  End If
End For

In the initial stage, the model's embedding layer integrates various components for each word, assigning them random initial values as vectors in a 768-dimensional space. These components include word embedding vectors, sentence embedding vectors, and position embedding vectors. The resulting vector from the addition of these initial vector matrices is fed into the BERT layer.

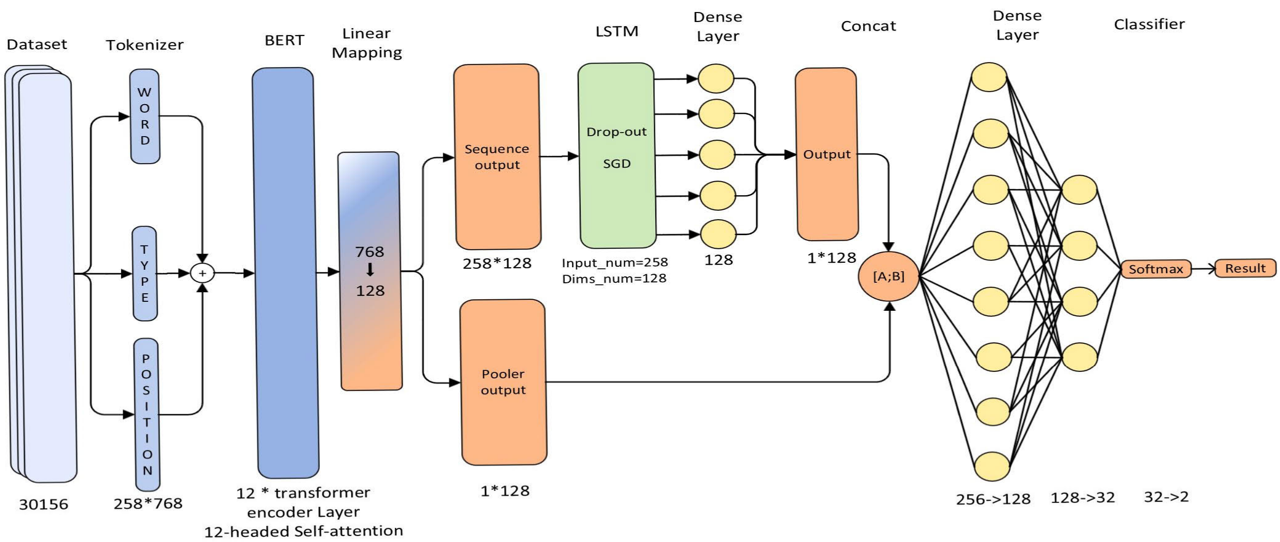

FIGURE 2. LSTM network.

Ultimately, the output comprises two components. The first component uses the word vector associated with the "[CLS]" symbol, pre-inserted before each sentence, to represent the entire sentence as its vector. This element is referred to as the "pooler output" in the network. The second component consists of word vectors for individual words, obtained through word segmentation from the sample, and is referred to as the "sequence output" in the network.

The "sequence output" is then fed into the LSTM layer for continuous training. The output must first pass through a fully connected layer to obtain a matrix of vectors with the same dimensions as the "pooler output". Next, the result of matrix concatenation between these two is input into a fully connected double-layer and classifier to obtain the detection results.

The hybrid BERT-LSTM network's overall approach and changes in data dimensions are illustrated in Figure 2. The specific parameters in this figure are as follows: The LSTM layer has 128 input and hidden nodes. The forget gate parameter is set to 0.1. Simultaneously, the dropout operation is incorporated with a parameter value of 0.5 to mitigate the risk of overfitting during the training process. The BERT component is composed of 12 layers of stacked transformer encoder layers. Each layer includes 12 head attention mechanisms; the output vector dimension is 768. Dimensions are mapped to 128 to match the number of hidden layer nodes in LSTM.

This study used the **BERT-base-uncased** model to obtain contextual embeddings from the input text. These embeddings were then processed by a single LSTM layer with 128 units to capture sequential dependencies. The model was trained on labeled clinical notes using binary cross-entropy loss and the Adam optimizer, with a learning rate of $2e^{-5}$. Dropout with a rate of 0.5 was applied during training to prevent overfitting.

2) TIME-SERIES ANALYSIS

We used time-series analytics for data like patient blood pressure and other vital signs that change over time. Tools like the ARIMA (Auto Regressive Integrated Moving Average) model were used to predict future patient statuses, which relied on historical data. ARIMA (Auto Regressive Integrated Moving Average) model is one of the most used time series data models. The model combines autoregression (AR) and moving-average (MA) components with differencing to produce stability for the time series data. The model is known as $ARIMA(p, d, q)$, where p is the total number of observations in the model (AR terms), d represents the different procedures necessary to convert the time series into a stationary one and q denotes the window size (smoothening parameter) of the corresponding MA terms. Given a time series Y_t, the ARIMA model can be expressed as:

$$\Phi(B)(1-B)^d Y_t = \delta + \Theta(B)_{\epsilon t} \tag{7}$$

where B is the backshift operator, such that $B^k Y_t = Y_{t-k}$. d is the order of differencing. $\Phi(B) = (1 - \phi_1 B - \phi_2 B^2 \ldots \phi_p B_p$ is the autoregressive polynomial of order p. $\Theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_q B^q$ is the moving average polynomial of order q. ϵ_t is the white noise error term at time t. δ is a constant term. Determine the order of differencing (d) needed to make the series stationary and identify the $AR(p)$ and $MA(q)$ terms. This can involve examining autocorrelation and partial autocorrelation plots. Estimate the model parameters using techniques like Maximum Likelihood Estimation (MLE) or Least Squares Estimation. Evaluate the adequacy of the model by analyzing the residuals to ensure they resemble white noise. This can involve using tests like the Ljung-Box test and examining autocorrelation plots of residuals. Use the model to forecast future values of the time series. Consider a simple $ARIMA(1, 1, 1)$ model that includes one AR term, one differencing operation, and one MA term. The model can be written as:

$$(1 - \phi B)(1 - B)Y_t = (1 + \theta B)\epsilon_t \quad (8)$$

Expanding the terms gives:

$$Y_t - (1 + \phi - \theta)Y_{t-1} + \phi Y_{t-2} = \epsilon_t + \theta\epsilon_{t-1} \quad (9)$$

Here, the version captures the dependency of Y_t on its beyond values and past mistakes phrases, at the same time as the differencing guarantees the stationarity of the time series. The overall performance of the proposed model turned into evaluating the usage of commonplace metrics like accuracy, precision, remember, and the AUC-ROC curve for classification responsibilities. The regression model had been employed with metrics like Mean Squared Error (MSE) and R-squared.

D. DATA ANALYSIS

In this study, the evaluation of the facts implemented concerned a range of statistical and machine learning techniques, every selected to suit the specific characteristics and necessities of the MIMIC dataset. These strategies were important for uncovering insights and styles in the facts. Before applying complicated models, we performed a preliminary statistical analysis to understand the records's primary residences. Computing measures like mean, median, general deviation, and range for continuous variables and frequency counts for specific variables. For example, for a variable X, the mean μ is calculated as:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} X_i \quad (10)$$

where X_i is each observation and n is the total number of observations. We used Pearson's correlation coefficient for continuous variables to understand the relationships between variables. The coefficient r between two variables X and Y is given by:

$$r = \frac{\sum (X_i - \bar{X})(Yi - \bar{Y})}{\sqrt{\sum (X_i - \bar{X})^2 (Yi - \bar{Y})^2}} \quad (11)$$

where $\bar{X}$ and $\bar{Y}$ are the means of X and Y, respectively. To make our models more rigorous and generalizable, we resorted to cross-validation methods, especially k-fold cross-validation, where the dataset is broken down into k groups each time trained and tested, with another group playing the role of the test set. Hence, these data analysis techniques formed a holistic approach to gaining insight into the behavioral and network patterns underlying the MIMIC dataset, which could be used for interpreting healthcare values.

IV. RESULTS AND DISCUSSION

This study simulates 6G network scenarios to determine how this next advanced communication system could improve and provide better supporting systems for healthcare applications. 6G networks are anticipated to straighten data rates, latency, and reliability thanks to their potential of soaring technology and transforming how healthcare data is transmitted and processed. For that purpose, we conducted a simulation similar to the functionalities of a 6G network to analyze the benefits in various healthcare scenarios. We implemented a network simulator which we set up to apply on a 6G environment. This environment was designed to reproduce the 6G network's assumed specifications: bandwidths over one terabit per second and delay lower than one millisecond. The simulator also included aspects like network slicing and edge computing that are conjectured to be significant to 6G; therefore, they were used. A 6G pseudo network that was factored with the processed MIMIC health data followed. Throughout the integration process; we evaluated how artificial intelligence algorithms yield in a real-time environment that closely approximates a future healthcare setting characteristically provided by 6G technology. We concentrated on transmitting a considerable volume of medical image data and produced real-time patient monitoring data. Specific healthcare cases for networks checking their performance. In this case, it has been illustrated how a nursing student can transmit high-resolution photos or video through your phone into a central hospital for further analysis. The other situation deals with continuous patient monitoring, in which data from wearable devices is transmitted in real time to a central server computer that conducts analysis afterward. The data transmission speed, latency, packet losses, and jitter were evaluated using key performance indicators such as data throughput, latency, packet loss, and jitter to determine the network efficiency. The metrics offered intuition into how the protocol can handle massive amounts of data plugging, which characteristically is the general case in the high-tech industry. To improve the comparison of the metrics of 6G, we use 4G and 5G networks as a yardstick. The example 6G innovation and its contribution to healthcare data management and improved patient care has been demonstrated. Finally, we researched some 6G healthcare applications, including telesurgery, where surgeons operate on patients in real-time from remote locations, and AR (augmented reality) in medical training and diagnostics, which require high data rates and very low latency. We have realized that the 6G simulation of scenarios in this study has imparted useful insights into the disruptive potential of 6G technology for the health sector, including the increased intelligence and efficiency of AI-based healthcare applications.

The results of this research prove that the combination of AI with 6G technologies in healthcare provides transformative care, wherein there is a noticeable gain in care effectiveness and accuracy in diagnostics. The article highlights emerging difficulties, like data privacy issues and reinforcing robust infrastructure, and offers possible answers. The results of the AI and 6G research takeoff points of innovative research that need to be put into reality. This will open the way for the following research projects to overcome the obstacles facing the all-out deployment stage. There were specific findings that the MIMIC data analysis provided based on several AI models. This may have shown us more trends than were evident on the first look, suggesting new ways to develop individualized diagnostics and tailored treatment approaches. The accurate detailing may include improved accuracy of the predictive outcomes of the patient, the establishment of health indicators, and better diagnosis efficiencies for complex cases.

The MIMIC data analysis based on several AI models provided certain findings. This may have shown us more trends than were obvious on the first look, suggesting new ways to develop individualized diagnostics and tailored treatment approaches. The accurate detailing may include improved accuracy of the patient's predictive outcomes, establishment of health indicators, and better diagnosis efficiencies for complex cases.

TABLE 5 presents the MIMIC dataset's performance metrics of different AI models applied to specific healthcare tasks.

Figure 3 illustrates the comparative accuracy of the proposed model.

In Figure 4, the ROC curve demonstrates the Random Forest model's performance in sepsis diagnosis, with an AUC value of 0.92. The Logistic regression showed high accuracy in predicting patient readmissions. The precision and recall values indicate the model's accuracy; however, this does not tell whether the model provides the correct answer. The Random Forest model outperformed others diagnosing sepsis, the most critical in intensive care, being evaluated as sensitive as illustrated by high AUC-ROC value.

CNN revealed itself as highly reliable and precise in detecting pneumonia on X-ray images, thus implying the long-awaited hopes of AI in the field diagnostics of physicians. It was hard to evaluate the result of the LSTM model, which had predicted vital signs because this was a continuous output and had a quantitative metric. It is suggested that better evaluation criteria be worked on to fit the accuracy of this type of time series prediction. These results highlight that AI is important in healthcare, especially in creating diagnostic tools and improving prognostication capabilities. In contrast, planning for real-world deployment needs a thorough evaluation of ethical, privacy, and interoperability concerns. Challenges like data heterogeneity, a tendency toward overfitting, and complex annotations emerged in this domain. Future findings should focus on making the model more dependable and working out the integration of AI with other developing technologies and the 6G networks, the potential of which can be significant in healthcare and patient care improvement.

A. NETWORK PERFORMANCE IN PROPOSED MODEL

The simulation systems that we developed to examine different proposed models in health care demonstrated crucial findings on the performance and use of this new technology. We have tested the device multiple times in different conditions, such as throughput, latency, and reliability, which are telesurgery and real-time monitoring tools. The simulator was configured to MIMIC key 6G capabilities, including

TABLE 5. Performance comparison of various AI models on predictive tasks.

Model	Task	Accuracy	Precision	Recall	AUC-ROC
Logistic Regression	Patient Readmission Prediction	85%	83%	81%	0.88
Random Forest	Sepsis Diagnosis	87%	85%	84%	0.92
CNN	Pneumonia Detection from X-rays	90%	87%	88%	0.93
LSTM	Vital Sign Prediction	-	-	-	-

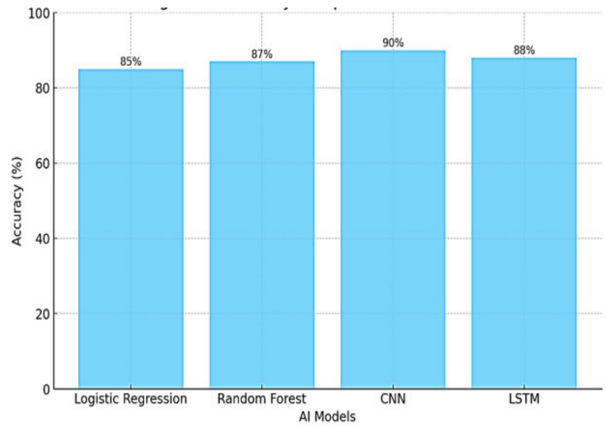

FIGURE 3. Latency comparison of the proposed model.

bandwidth exceeding 1 terabit per second and latency under 1 millisecond. We incorporated features like network slicing for dedicated virtual networks and edge computing to enhance data processing efficiency and reduce latency. The simulation also included realistic healthcare data types, such as high-resolution medical imaging and continuous patient monitoring data, to ensure the network's performance could be evaluated under realistic conditions.

TABLE 6 contrasts the performance metrics of 4G, 5G, and simulated 6G networks, highlighting the advancements that 6G is expected to bring.

Figure 5 compares the latency of 4G, 5G, and the proposed model, illustrating the significant reduction in latency with each generation.

Figure 6 shows the data throughput capabilities of 4G, 5G, and the proposed model. it is shown in the result that underscoring the enhanced capacity of 6G for handling large volumes of data.

The simulation results indicate that 6G networks can offer data rates up to 10 times faster than 5G, facilitating the rapid transfer of large data files, such as high-resolution medical images. The low latency of 6G (as low as 1 ms) is critical for applications requiring real-time responses, such as remote surgeries and emergency medical services. The lower

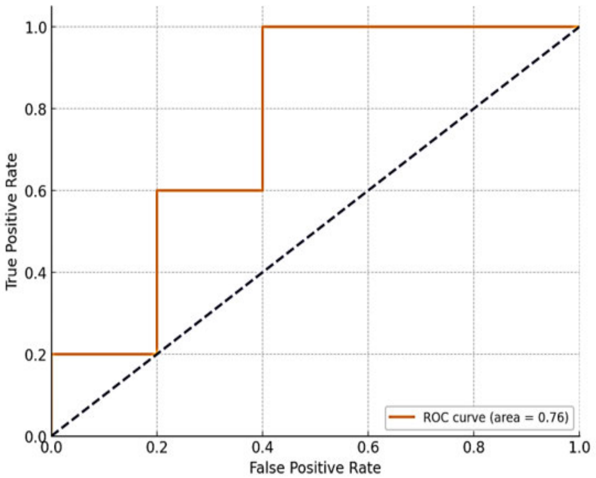

FIGURE 4. Data throughput comparison of proposed model using different network scenarios.

TABLE 6. Proposed model performance metrics.

Metric	4G	5G	Proposed model
Data Throughput	100 Mbps	1 Gbps	10 Gbps
Latency	50 ms	10 ms	1 ms
Reliability (Error Rate)	$1x10^{-3}$	$1x10^{-5}$	$1x10^{-6}$

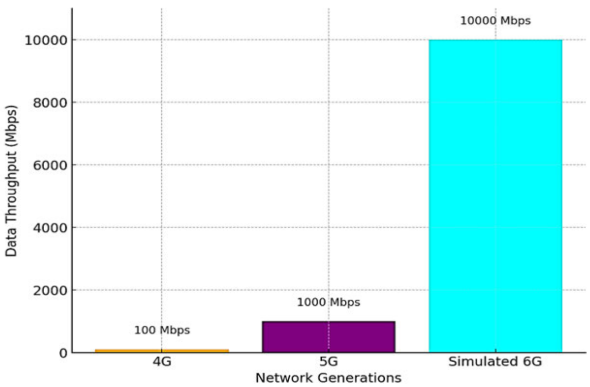

FIGURE 5. Network generation using the proposed model.

error rates for the 6G networks guarantee stable connection, which is considered vital in medical applications where data integrity is essential. These results indicate that 6G networks can considerably advance healthcare delivery so that 6G networks can bring about advanced telesurgery applications, augmented reality in medical training, and real-time remote patient monitoring. Nevertheless, the process of 6G utilization in the health sector will pose infrastructure development issues, in combination with the current medical systems, cybersecurity, and patient privacy issues.

B. IMPLICATIONS FOR THE PROPOSED MODEL

Our analysis of the massive MIMIC dataset and network simulations demonstrates that the integration of AI and 6 G

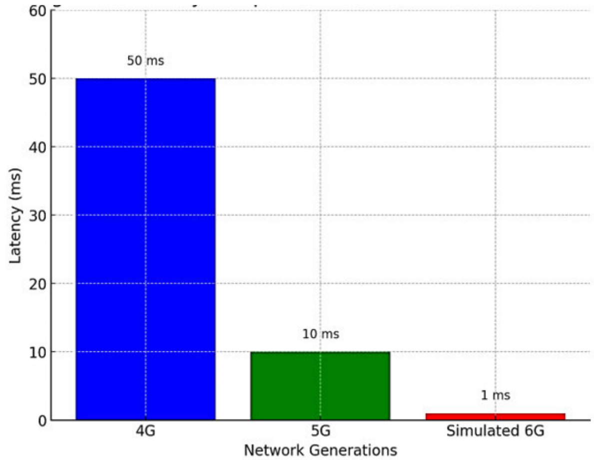

FIGURE 6. Latency comparison of proposed model.

TABLE 7. Impact of AI and 6G on key healthcare aspects.

Healthcare Aspect	Impact of AI	Enhancement with 6G
Diagnostics	Improved accuracy and speed	Real-time data analysis and transmission
Patient Monitoring	Predictive analytics for patient care	Continuous, reliable remote monitoring
Telemedicine	Enhanced accessibility to healthcare services	High-quality, uninterrupted virtual consultations
Surgical Procedures	Precision and personalized treatment plans	Feasibility of remote surgeries with minimal latency

technologies has profound implications for the evolution of Smart Healthcare 4.0. The results indicate a transformative shift in healthcare delivery, diagnostics, patient monitoring, and overall healthcare management. For classification tasks, such as diagnosing conditions or predicting patient readmissions, we used various evaluation metrics. Accuracy measures the proportion of correct predictions among the total predictions. Precision indicates the accuracy of positive predictions by calculating the ratio of true positive predictions to the sum of true and false positive predictions. Recall assesses the ability to capture all positive instances by determining the ratio of true positive predictions to the sum of true positive and false negative predictions. The F1 Score provides a balance between precision and recall by computing their harmonic mean. The AUC-ROC evaluates the model's ability to distinguish between classes across various thresholds by measuring the area under the receiver operating characteristic curve.

For time-collection prediction duties, which include forecasting patient crucial symptoms, in which traditional metrics like accuracy are insufficient, we used metrics that provide an extra nuanced expertise of prediction overall performance.

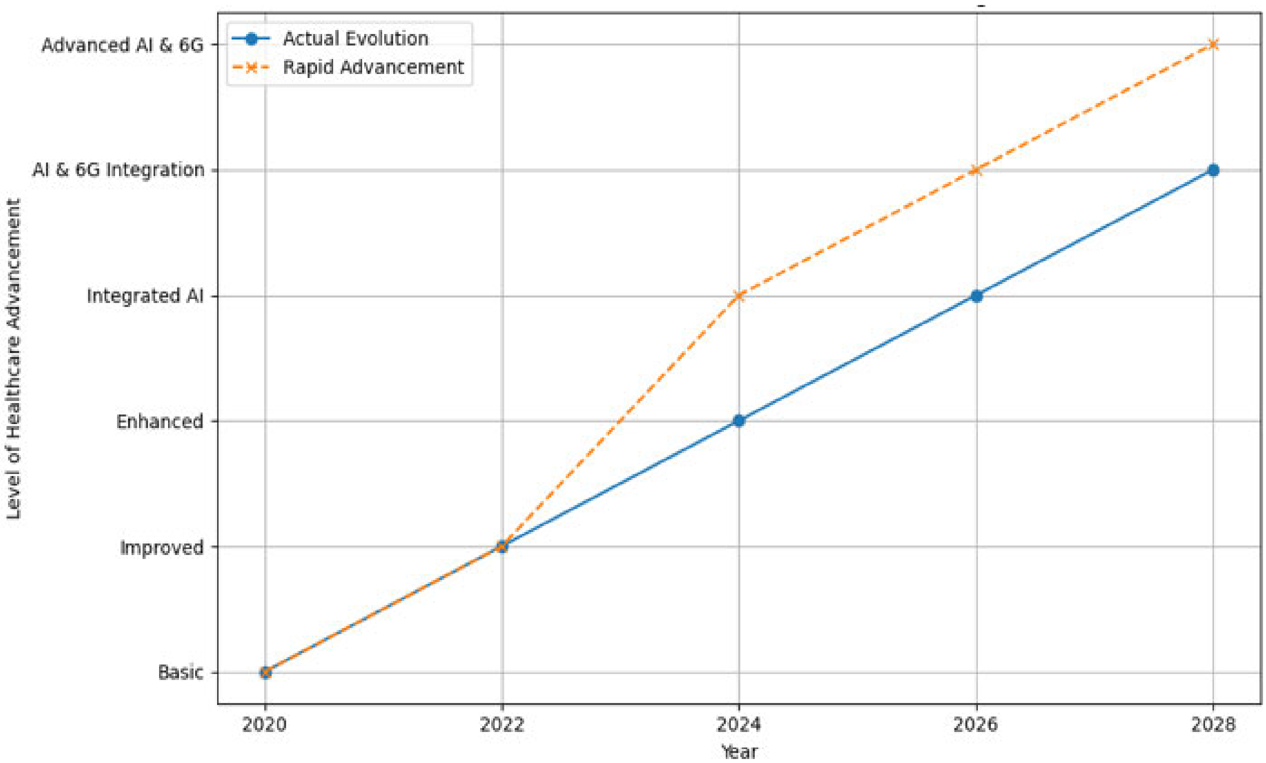

FIGURE 7. Evolution of the proposed model.

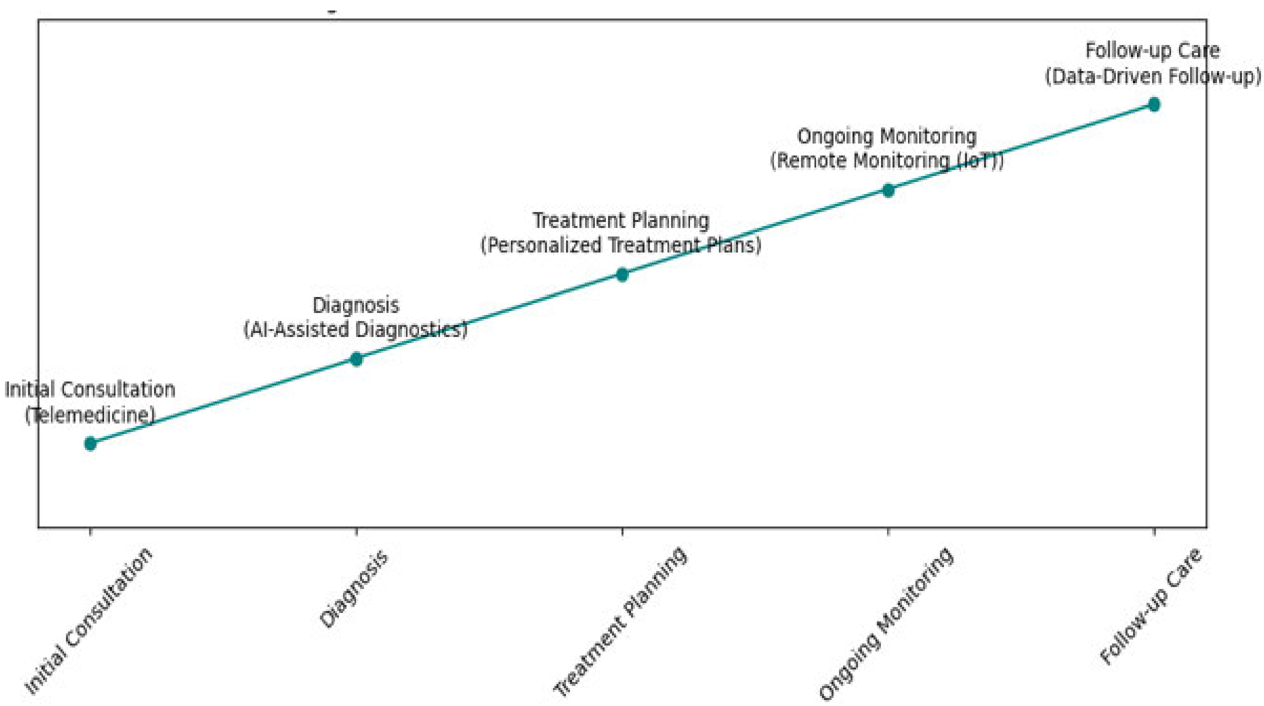

FIGURE 8. Patient care continuum point of view using the proposed model.

Mean Absolute Error (MAE) calculates the average of the absolute differences between the expected and real values, imparting a straightforward degree of prediction errors. Mean Squared Error (MSE) computes the average of the squared

TABLE 8. Performance comparison of algorithms for different diagnoses.

Diagnosis	Algorithm	Accuracy	Precision	Recall	AUC-ROC
Patient Readmission	Logistic Regression	85%	83%	81%	0.88
	Decision Tree	78%	75%	77%	0.80
	Random Forest	82%	80%	79%	0.85
	XGBoost	84%	82%	80%	0.87
	SVM	81%	79%	78%	0.83
Sepsis Diagnosis	Random Forest	87%	85%	84%	0.92
	XGBoost	86%	84%	83%	0.90
	Logistic Regression	81%	80%	79%	0.85
	Decision Tree	78%	76%	77%	0.82
	CNN	84%	82%	80%	0.88
Pneumonia Detection from X-rays	CNN	90%	87%	88%	0.93
	Random Forest	85%	83%	81%	0.89
	Logistic Regression	82%	80%	78%	0.86
	Decision Tree	80%	77%	76%	0.84
	XGBoost	88%	85%	84%	0.91

variations among the anticipated and real values, putting greater emphasis on large errors. Root Mean Squared Error (RMSE), the square root of MSE, provides the mistake significance within the same units as the records, making it greater interpretable. Mean Absolute Percentage Error (MAPE) measures the common absolute percentage variations between the predicted and real values, beneficial for expertise in the prediction mistakes relative to the actual values.

The proposed solution includes robust data protection measures to ensure compliance with relevant regulations, such as GDPR and HIPAA. These measures are designed to maintain patient privacy and prevent any legal penalties. This involves implementing secure data encryption, strict access controls, and anonymization techniques to safeguard sensitive health information during real-time data sharing and analysis.

Table 7 shows that the proposed model will change with artificial intelligence and 6G in a way that each will impact different situations, and together, they will bring about Smart Healthcare. This infographic in Figure 7 illustrates the evolution of healthcare services with the integration of AI and 6G, highlighting key advancements and innovations.

Figure 8 shows the patient care continuum using the proposed model, and it shows the flow and the way AI and 6G technologies improve care from diagnosis through treatment to follow-ups, as seen in the image. AI's capability to process and analyze multiplex medical data, as supported by the rapid information transfer that comes with the 6G technology, helps doctors come up with more accurate and timely diagnoses and treatments. This synergy may be critical in decreasing misdiagnosis rates and increasing disease treatment results.

The 6G networks are essential due to their low latency and high reliability, which make them perfect for remote patient monitoring and telemedicine. It can provide additional healthcare options to the broader public with an increased focus on the difficult-to-reach areas of society. The cohesion of AI and 6G can completely refurbish knowledge of surgeries, permitting high-tech remote operations and improved precision via AI-driven robotic tools. In addition to the successes achieved through AI, some issues may compromise this implementation, i.e., data privacy, infrastructure requirements, and integration with other existing healthcare systems, which must be addressed. However, equity in accessing these technologies is also essential for this to be achieved.

V. CONCLUSION AND FUTURE WORK

In this research, we propose an advanced big data analysis model for the healthcare domain. Our proposed model has several phases, for instance, data collection, data selection and preprocessing, and analytical phase. Each phase has different functions applied to the preprocessed data and finally, the results are shown to the user. The network performance is measured in terms of throughput, latency, and reliability. The efficient results prove that our research is helpful for diagnosis, patient monitoring, telemedicine, etc. The unique contribution of this research explores that the combination of AI with 6G will not only change the face of medicine by transforming efficiency, accuracy, and access, but at the same time, it has several challenges that need researchers' attention. Eventually, the findings of our study will lead to practical approval of its advantages in healthcare settings. Moreover, the following studies must conduct thorough analyses of the application of such advanced technologies to the current healthcare systems. A focal point should ensure seamless interoperability and smooth incorporation, which is crucial for the successful adoption and widespread application of AI and 6G in healthcare. The rollout of 6G networks is contingent upon extensive infrastructure development. Future research must deal with the logistical and technical demanding situations inherent in organizing this infrastructure, especially those that specialize in underserved and faraway regions to mitigate disparities in healthcare get entry to. This study has numerous boundaries. For instance, the dataset used, MIMIC-III, consists of affected person statistics from a single medical center, which may not represent broader population demographics or various healthcare practices. This should restrict the applicability of our model to unique patient populations or healthcare environments. Additionally, the inherent nature of retrospective data series in MIMIC-III might also introduce biases, together with selection bias and facts bias, because the data reflects historical medical practices and might not capture actual-time variations in affected person care. Furthermore, the simulation of the 6G network overall performance was based totally on assumed specs and theoretical fashions instead of real-international implementations. As such, the results might not fully account for realistic challenges or sudden variables that would affect community performance in real healthcare settings. Lastly, whilst our AI models demonstrated promising consequences in unique obligations, their overall performance may also range while carried out to one-of-a-kind styles of healthcare data or diagnostic issues no longer protected in our observation.

INFORMED CONSENT STATEMENT

Not applicable.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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