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Research Article

AI and Patient Data Sovereignty: Researching the Implications of AI on Patient Data Ownership, Control and Consent

Vivek Yadav*

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***Corresponding author:** Vivek Yadav, USA, E-mail: Yadav.Vivek@myyahoo.com

ABSTRACT

The overall chapter mainly highlights the powerful developments in medical care that improve the traditional symptom practice in medicine. It identifies the best pathway of personalised medicine for the patient's analyses patient information and monitors health factors with AI inclusion. This research identifies the complexity of the disease and identifies the difficulty of healthcare decisions to minimise technological advancements. Further, in order to analyse the health records and patient data use different analytical tools and approaches to addressing the social and ethical issues in the privacy protection of healthcare data.

Keywords: Big Data, Healthcare, Patient data, AI and machine learning models, Privacy, Algorithm bias

1. Introduction

The integration of AI for significant healthcare implications and improved patient data sovereignty mainly focuses on deploying consent, ownership and control. The continuous development and advancement of AI technology uplift healthcare both opportunities and challenges. AI has the potential to improve patient care by properly enhancing of data management process, providing personalised treatment plans and improving the diagnostics process[1]. The main key challenges faced by the patient are that unethically using the patient data mainly avoids innovation roadblocks and legal entanglements. The major complexity between the adaptive data storage solutions and "data sovereignty laws demand" is fascinating seamless data mobility. On the other hand, AI use is a healthcare necessity has created ethical issues in the improvement of the robust consent mechanism and transparency in managing patient data. The patients, professional and legal team are establishing a proper governance framework that creates advancement of technology with ethical standards. This approach provides a safeguard of the patient data and also fosters the data-driven AI solution in healthcare for enhanced data sovereignty.

2. Aims and Objectives

Aim

The research aims to perform a detailed analysis regarding improving patient data protection and evaluating the usefulness of AI in maintaining data sovereignty with a particular emphasis on control ownership and permission.

Objectives

- To illustrate the use of AI in data management procedures and healthcare outcomes using machine learning implementation.
- To determine the area of research where the functions and effects of AI on patient data sovereignty are lacking.
- To utilise Python libraries to perform visualisation regarding data privacy trends and patterns to analyse the importance of data ownership in the context of AI.

Scope

The extent of this examination envelops a top-to-bottom investigation of the convergence between computerized reasoning (artificial intelligence) and patient information sway in medical care. With man-made intelligence progressively coordinated into medical care frameworks, it is critical to address the moral, lawful, and innovative difficulties related to patient information on the board [2]. This exploration intends to assess how man-made intelligence can upgrade patient information security, zeroing in on information possession, control, and assent. It analyses the on-going utilization of simulated intelligence advances like AI, normal language handling, and prescient examination in overseeing patient information and further developing medical care results. Moreover, the exploration recognizes holes in existing writing in regard to the effect of artificial intelligence on information sway and investigates the adequacy of different information protection techniques, for example, encryption and differential security in defending patient data [3].

2. Background

Strengthened and sped up ratification and computerization are getting expanded consideration in wellbeing settings. The subsequent intricacy is explored by applications to handle enormous information, for example, AI or man-made consciousness, frequently as a component of a guarantee to drive the personalization of well-being administrations. Additionally, information-driven and mechanized apparatuses are commonly concocted to complete exceptionally unambiguous errands, tending to specific previews of clinical practice. By this, the testing and refinement of such devices ordinarily happen in somewhat restricted and practically counterfeit situations in which specific originations of framework execution, e.g., concerning awareness and particularity of demonstrative order, are contrasted and the exhibition of human clinicians [4].

A further issue of worry regarding wellbeing-related information is the broad requirement for patient information for the turn of events and refinement of instruments in a perfect world propelling exploration, care, and the benefit of everyone from one viewpoint, and conceivable protection issues on the other. To gain ground on these issues, the viewpoints of patients and clinical specialists utilizing and sending enormous information applications are an unmistakable wellspring of information. They can contribute direct decisions of possibilities and difficulties in tackling wellbeing-related information. These partners work and connect concerning clinical work processes that are progressively formed and changed by these new innovations.

3. Literature Review

AI and ML in health intelligence, resource management and precision medicine

Intelligent big data platforms are crucial for improving the quality and advancement of medical care by enabling the analysis of dynamic hidden patterns within clinical data using AI algorithms to obtain valuable insights about patients for early detection and prevention of chronic diseases like cancer, and facilitating seamless information sharing by establishing efficient communication across medical service units and research laboratories.

Its application in medical services could be one more extraordinary jump in medication and a groundbreaking power for directing customized and populace medication with a few computational advantages. In the past, various computer-based intelligence and ML-based endeavours have been made for unravelling sicknesses to work with prescient findings and subsequently guide therapy factors, for example drawing illness connections utilizing clinical appearances, EHR and information created utilizing wearable innovation [5]. Knowledge of well-being can play a crucial role in various stages of clinical exploration and investigation, leading to significant advancements in achieving the goals of delivering better personalized and population-based healthcare. In the past decade, diverse operational and research-oriented medical services information management and scientific frameworks have been developed within both academic and commercial sectors.

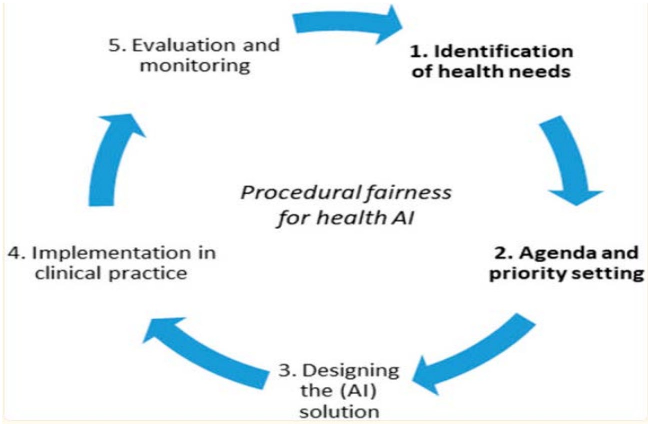

Figure 1: Procedural fairness for health AI.

ML in medicine provides better patient interaction

This technique centres on examining the principal primary changes by the medical services frameworks expected to completely understand the capability of AI in medication. It puts serious areas of strength for growing the standards of AI (ML) in medication, which may revolve around the thought of individualized finding and treatment in light of all suitable patient information as well as shared encounters. For administrative and billing purposes, it works well with EHRs, which might keep them from giving their patients the best treatment possible [6]. However, they also asserted that the incorporation of machine learning into electronic health records might raise concerns about over-reliance and result in a decline in mistakes and automation bias awareness. Utilizing a preparation AI classifier in electronic well-being records (EHRs) for design identification, specialists would have the option to foresee future occasions in high-risk patients, get a complete and precise determination, and immediately find significant data in understanding diagrams with less clicking, voice transcription, and worked on prescient composing [7]. The construction of models for the segmentation and interpretation of physiological data, the prediction of illness progression, and radiological diagnosis are based on support vector machines (SVMs) and deep learning. Making proficient models to assist with determination in view of information looking like specific sicknesses, as well as picture examination and translation to upgrade specialists' capacity to decide. The creators additionally raised moral issues with the utilization of ML, mostly about large information administration and the board and the eventual fate of work [8].

Overview of Remote Patient Monitoring (RPM) Systems

Remote Patient Monitoring (RPM) systems can be understood as an innovative concept in contemporary health care that utilizes technology to track patients' conditions outside conventional health care facilities [9]. Through provide devices and sensor, RPM systems capture precise medical and health data of person in real-time. Such data is conveyed to other treating physicians or facilities to monitor the health status of a patient over a given period. This is more so given the currents trends of having limited health care facilities and practitioners especially in the rural setting a reason why RPM systems are more important. Through the supervising of patients via RPM systems, the involved healthcare providers are able to ensure that patients receive appropriate medical care, pointing to the fact that the gap in accessibility to healthcare is closed through minimal, infrequent, and long travels to healthcare centers. Advancements in technology have also improved RPM systems in that their ability to perform duties has been boosted. Initial RPM systems centered on simple biometric values for such essential parameters as pulse and blood pressure. However, these days the complexities of chronic afflictions such as diabetic, cardiovascular diseases, and respiratory ailments have broadened the area to entail thorough tracking [23]. Increased advances mean that today's RPM platforms can incorporate data from wearable technology, mHealth applications, and smart home technologies giving a full view of a patient's health condition.

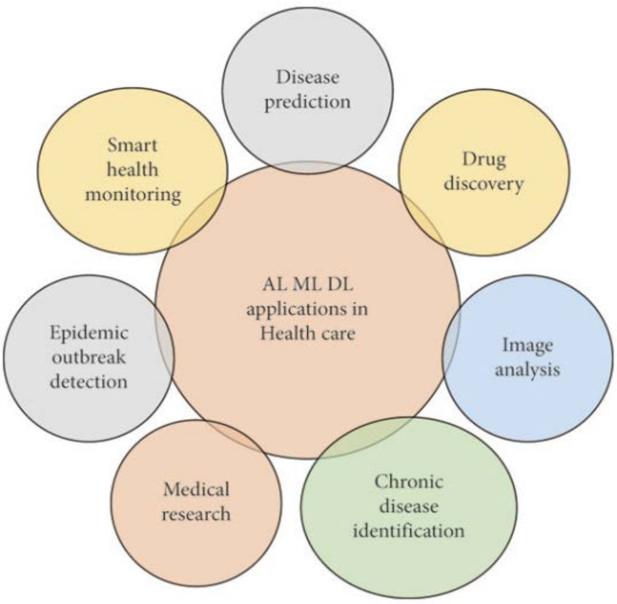

Figure 2: AI application in healthcare.

The literature of previous work indicates that RPM systems enhance patient positive results. They improve the control of chronic illnesses by providing information that can be utilized in early identification of other health complications [10]. It can help decrease the number of hospitalizations, emergency department visits as well as enhance the use of prescription drugs and increase patients' satisfaction. Therefore, RPM systems can be considered as a valuable technological advancement in the delivery of health care services especially in the rural areas where such services however limited are very important. RPM systems result in better quality, improved health outcomes and efficient healthcare delivery through the use of advanced technology for constant monitoring of patients' health.

Role of Artificial Intelligence in RPM Systems

AI is critical in improving RPM systems through advanced features that boost the efficiency of patient care and management. As RPM systems are developed and integrated into an individual's life, machine learning, predictive analytics, and natural language processing are applied to optimize the outcome and efficiency of an AI RPM system. AI improves diagnosis in RPM by studying large amounts of patients' data searching for patterns and looking for signs of certain diseases [11]. For instance, basic artificial intelligence functionality involves an ability to identify future indicators of chronic diseases including heart diseases and diabetes using data on the variations in patient's vital clinical processes. This early detection enables prevention mechanism to be instituted and this is very important in preventing the worsening of these health conditions. Also, AI relieves the constant monitoring processes that strain healthcare providers and minimizes their intensity concerning more significant issues of patient care [12].

In terms of predictive analytics, it can predict a patient's decline in health status, which if tackled before reaching such a state, can save a hospitalization. Another benefit realized from AI implementations in RPM systems is that suggestions provided to patients can also be modified depending on that patient's information leading to more compliance to the prescribed therapies and enhanced health conditions. However, the integration of AI in RPM systems has its constraints especially in the rural areas as pointed out below. New challenges related to technology, including restricted access to the internet and digital gap; have to be solved to employ AI in full. Nevertheless, the incorporation of AI into RPM systems is a remarkable improvement in the advancement and development of health systems since it promotes health monitoring and come up with solutions before the patients' conditions worsen.

Challenges and Limitations of Implementing AI in Rural RPM

The use of AI in RPM in rural regions has multiple major challenges and restrictions, which need future further discussion to reveal how these technologies could boost the results of healthcare administration. The first one is the technological factor as it is quite hard to introduce RCM in high-tech organizations. A lot of such strategies do not have the requisite infrastructure; especially internet connection and modern digital devices required for AI-supported RPM systems. This digital divide inhibits the further establishment and efficient implementation of these systems and consequently, their extent of influence. Another issue is that of data privacy and security; it is a challenge that has inevitably cropped up because of the growing use of artificial intelligence [22]. AI systems in RPM depend on the constant amassing and sending of vital and in many cases personal health information. It is imperative that the data is kept highly secure due to the potentially poor levels of cyber security awareness and or resources in many rural geographic locations. Any compromise can result in a severe problem of privacy infringement and consequently, people's distrust of such technologies.

However, the consummation and functionality of AI technologies lay another level of issues ahead. Patients and healthcare providers in rural are may not have proper training and may not be aware of the AI-tools available. This can lead to some backlash as well as the challenge of implementing such interventions into the standard operating procedures of care delivery. To eliminate the above barriers, it is crucial to focus on the right training and support systems. Also, the capital required to implement the AI system and its maintenance may be very expensive for a number of rural healthcare facilities. Lack of funds in these regions also contributes to the situation where it is impossible to introduce the latest AI equipment without the help of external capital [21]. Thus, AI has the capacity of revolutionizing RPM systems if some of this technological, security, adoption and financial issues are fixed to ensure that AI is implemented in rural health facilities.

Case Studies and Success Stories

A number of examples and success stories are provided to explain the use of AI and Remote Patient Monitoring (RPM) system in rural area showing that how this innovation enhances the possibility of effective medical facilities in the suburban regions. An example of such RPM implementation can be viewed in rural areas in India where AI was used to track patient with chronic diseases such as diabetes and hypertension. What the system could do with real-time data collected from wearable devices was to use machine learning algorithms to predict certain heath complications [13]. It enabled timely identification of patients and their conditions thus enabling care givers to prevent escalation of patient status hence reduction in hospital admissions and emergency visits. Industry experts said that the project was a success because of active collaboration between healthcare workers and technology suppliers for appropriate preparations for using the new technologies.

In another case, a pilot project in rural Kenya in the use of artificial intelligence RPM systems to manage maternal health [14]. Part of the expectant mothers wore monitoring gadgets that recorded their condition and relayed it to a main unit. The data was subsequently forwarded AI algorithms where potential dangers like preeclampsia and gestational diabetes were established. Hence increased rate of early and timely interventions meant better maternal and neonatal health. The results of the program reflected the willingness of the communities and the inclusion of traditional birth attendants into the monitoring system between the technology and the culture of the program. In America, a rural connected healthcare system in Mississippi utilized AI-based RPM for patients with heart failure [16]. It included care suggestions and notifications that seem relevant to the client's constant monitoring data. Organization also reported of reduced readmissions whose required the services of a hospital and also indicated that their quality of life improved. The outcome of this program indicated the need to integrate proper training programs coupled with patient awareness in the usage of AI technology [15]. These cases explain how AI integrated RPM systems have the ability of boosting the rural health care systems through timely provision of intervention based on patient data.

4. Theoretical Framework

The context of this research in patient data sovereignty with AI, it mainly ensures differential privacy and provides sensitive patient information by confidential AI algorithm process for analysing of large dataset of healthcare insights. Further addition of noise data controlled and make individual privacy by aligning with legal and ethical AI deployment are help to mandate data protection measure.

5. Methodology

Research methods

This research mainly focuses on experimental research methods to analyse patient data and try to minimise the ethical issues with the collection of big data. Furthermore, methods for quality assurance and data validation are purposefully used to guarantee the accuracy of the measurements and data [20]. In a similar vein, the outcomes of data analysis support decisions made about resource allocation and intervention in healthcare systems. In this research method, used ML and AI that provide different algorithms for learning different data variables and making relationships with data features that help to support in the decision-making process.

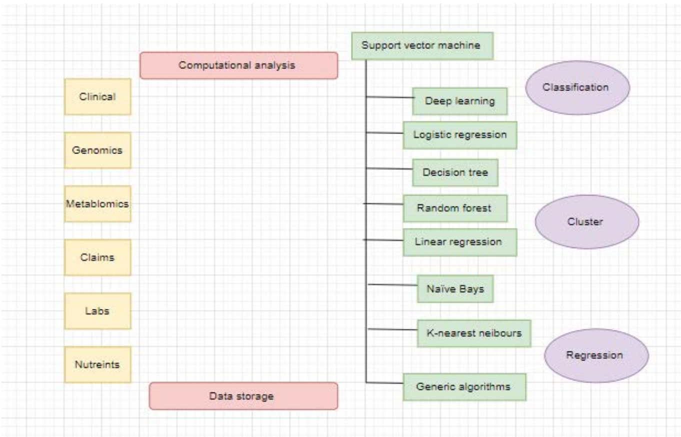

Figure 3: Diagram for research methods.

Data collection

The data are collected by using different machine learning models and doing different graphical representations such as exploratory analysis, heat map and do predictive analysis [19]. Through this analysis, the main data are collected about real-time patient monitoring, analysis the disease pattern, diagnosis prescription of medicine and enhance the treatment process. In order to collect the data, it has mostly used SVM, logistic regression, random forest, linear regression and so on. The selection of the SVM approach helps to generate a trained classifier and decision boundaries. It mainly analyses symptom classification and improves the diagnostic analysis.

Ethical consideration and framework

Doing the overall research and properly progress the experiment, it must be required to maintain proper ethics in overall research [17]. Firstly, collect the dataset of the patient data from authentic sources and must have to pre-processing the data and remove the null values. Further must ensure that the patient is informed about how their data is used for safeguarding in place.

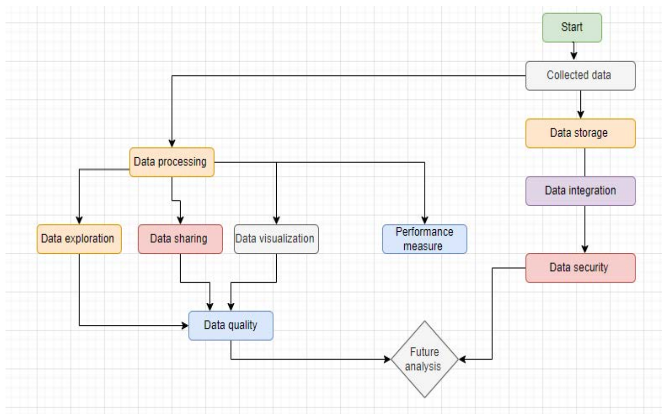

Figure 4: Diagram of ethics maintain.

Further, it must employ data protection measures by encryption of data and reducing the chance of unauthorised access and breaches. It is further also ensured that AI algorithms are free from biases in unethical treatment of patients [18]. This must be implemented in proper AI-driven healthcare decisions.

Tools and technique

Different tools and techniques have been used to do the experiment and analyse the patient data. Deep learning techniques have been used to learn complex relationships between heterogeneous clinical data and features. It is implemented for predictive modelling and identifies the pattern of recognition. On the other logistic regression is also used for real-time implementation of medicine for the complex disease process and to identify the relationship between the continuous variables and predictor categorical.

6. Chosen Dataset

https://www.kaggle.com/datasets/saurabhshahane/in-hospital-mortality-prediction/data

7. Result

Uses of artificial intelligence and big data are becoming increasingly important in various health domains. The moral and societal issues raised by these technological advances have already been extensively studied.

```
   group      ID  outcome  age  gendera        BMI  hypertensive  \
0      1  125047      0.0   72        1  37.588179             0
1      1  139812      0.0   75        2        NaN             0
2      1  109787      0.0   83        2  26.572634             0
3      1  130587      0.0   43        2  83.264629             0
4      1  138290      0.0   75        2  31.824842             1

   atrialfibrillation  CHD with no MI  diabetes  ...  Blood sodium  \
0                   0               0         1  ...    138.750000
1                   0               0         0  ...    138.888889
2                   0               0         0  ...    140.714286
3                   0               0         0  ...    138.500000
4                   0               0         0  ...    136.666667

   Blood calcium    Chloride  Anion gap  Magnesium ion     PH  Bicarbonate  \
0       7.463636  109.166667  13.166667       2.618182  7.230    21.166667
1       8.162500   98.444444  11.444444       1.887500  7.225    33.444444
2       8.266667  105.857143  10.000000       2.157143  7.268    30.571429
3       9.476923   92.071429  12.357143       1.942857  7.370    38.571429
4       8.733333  104.500000  15.166667       1.650000  7.250    22.000000

   Lactic acid  PCO2  EF
0          0.5  40.0  55
1          0.5  78.0  55
2          0.5  71.5  35
3          0.6  75.0  55
4          0.6  50.0  55

[5 rows x 51 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1177 entries, 0 to 1176
```

Figure 5: Utilised dataset.

As per the need of the project, the first step is responsible for demanding a thorough data cleaning process so that it can further identify the missing values present within and it can further impact the analyses related to health outcomes. Enhancing the integrity of data through appropriate handling of missing values provides accurate insights while performing the analysis of healthcare data.

Exploratory data analysis becomes essential in providing foundational insights regarding the characteristics of the dataset which also includes descriptive statistics.

The healthcare data set's measurements have been depicted with the use of thorough descriptive statistics.

The graphs are capable of determining the trends as well as patterns present within the dataset at ease as per the requirement of the analysis. As per the above graph, it is capable of determining the age distribution associated with the data. It gives a clear picture of the demographic profile of patients and becomes crucial as ageing is frequently associated with health issues and sometimes affects attitudes towards data ownership in a medical context. This is further capable of determining the age groups or outliers within a particular age range.

```
+ Code  + Text
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   group                     1177 non-null   int64
 1   ID                        1177 non-null   int64
 2   outcome                   1176 non-null   float64
 3   age                       1177 non-null   int64
 4   gendera                   1177 non-null   int64
 5   BMI                       962 non-null    float64
 6   hypertensive              1177 non-null   int64
 7   atrialfibrillation        1177 non-null   int64
 8   CHD with no MI            1177 non-null   int64
 9   diabetes                  1177 non-null   int64
 10  deficiencyanemias         1177 non-null   int64
 11  depression                1177 non-null   int64
 12  Hyperlipemia              1177 non-null   int64
 13  Renal failure             1177 non-null   int64
 14  COPD                      1177 non-null   int64
 15  heart rate                1164 non-null   float64
 16  Systolic blood pressure   1161 non-null   float64
 17  Diastolic blood pressure  1161 non-null   float64
 18  Respiratory rate          1164 non-null   float64
 19  temperature               1158 non-null   float64
 20  SP O2                     1164 non-null   float64
 21  Urine output              1141 non-null   float64
 22  hematocrit                1177 non-null   float64
 23  RBC                       1177 non-null   float64
 24  MCH                       1177 non-null   float64
 25  MCHC                      1177 non-null   float64
 26  MCV                       1177 non-null   float64
 27  RDW                       1177 non-null   float64
 28  Leucocyte                 1177 non-null   float64
 29  Platelets                 1177 non-null   float64
 30  Neutrophils               1033 non-null   float64
 31  Basophils                 918 non-null    float64
 32  Lymphocyte                1032 non-null   float64
 33  PT                        1157 non-null   float64
 34  INR                       1157 non-null   float64
```

Figure 6: Checking the data types.

```
None
             group             ID      outcome          age      gendera  \
count  1177.000000    1177.000000  1176.000000  1177.000000  1177.000000
mean      1.299065  150778.120646     0.135204    74.055225     1.525064
std       0.458043   29034.669513     0.342087    13.434061     0.499584
min       1.000000  100213.000000     0.000000    19.000000     1.000000
25%       1.000000  125603.000000     0.000000    65.000000     1.000000
50%       1.000000  151901.000000     0.000000    77.000000     2.000000
75%       2.000000  176048.000000     0.000000    85.000000     2.000000
max       2.000000  199952.000000     1.000000    99.000000     2.000000

              BMI  hypertensive  atrialfibrillation  CHD with no MI  \
count  962.000000   1177.000000         1177.000000     1177.000000
mean    30.188278      0.717927            0.451147        0.085811
std      9.325997      0.450200            0.497819        0.280204
min     13.346801      0.000000            0.000000        0.000000
25%     24.326461      0.000000            0.000000        0.000000
50%     28.312474      1.000000            0.000000        0.000000
75%     33.633509      1.000000            1.000000        0.000000
max    104.970366      1.000000            1.000000        1.000000

          diabetes  ...  Blood sodium  Blood calcium     Chloride  \
count  1177.000000  ...   1177.000000    1176.000000  1177.000000
mean      0.421410  ...    138.890016       8.500894   102.283835
std       0.493995  ...      4.151347       0.572263     5.339733
min       0.000000  ...    114.666667       6.700000    80.266667
25%       0.000000  ...    136.666667       8.148864    99.000000
50%       0.000000  ...    139.250000       8.500000   102.500000
75%       1.000000  ...    141.600000       8.869063   105.571429
max       1.000000  ...    154.736842      10.950000   122.526316

         Anion gap  Magnesium ion          PH  Bicarbonate  Lactic acid  \
count  1177.000000    1177.000000  885.000000  1177.000000   948.000000
mean     13.925094       2.120169    7.378532    26.911766     1.853426
std       2.652732       0.251532    0.067320     5.167512     0.983819
min       6.636364       1.400000    7.090000    12.857143     0.500000
```

Figure 7: Descriptive Statistics.

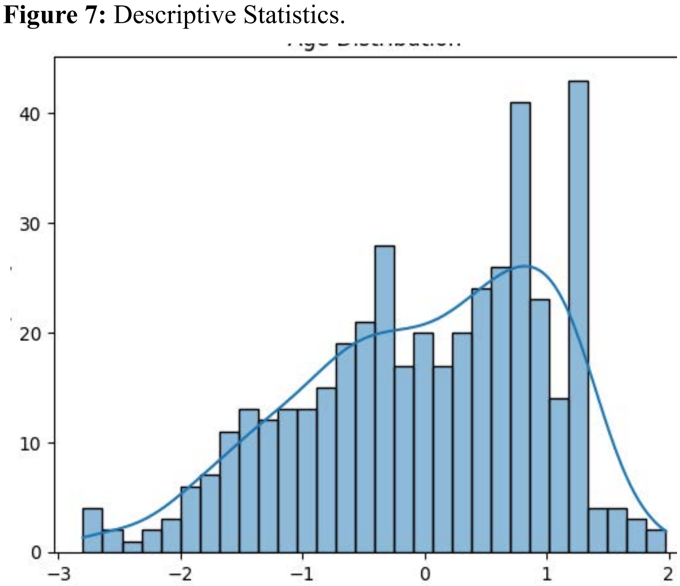

Figure 8: Exploratory graphs.

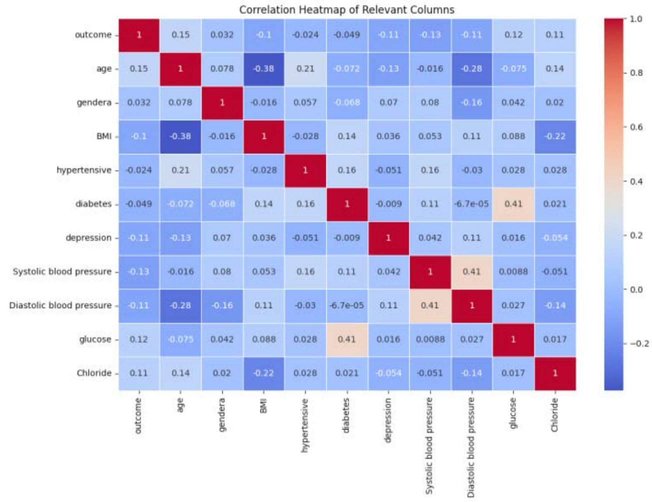

Figure 9: Heat map for correlation analysis.

The relationship among all the variables in the dataset has been determined with the use of correlation evaluation. The pattern within the indicator has been determined using trend analysis. Coefficient and direct/ indirect trends are capable of illustrating the coherence to display using the heatmap.

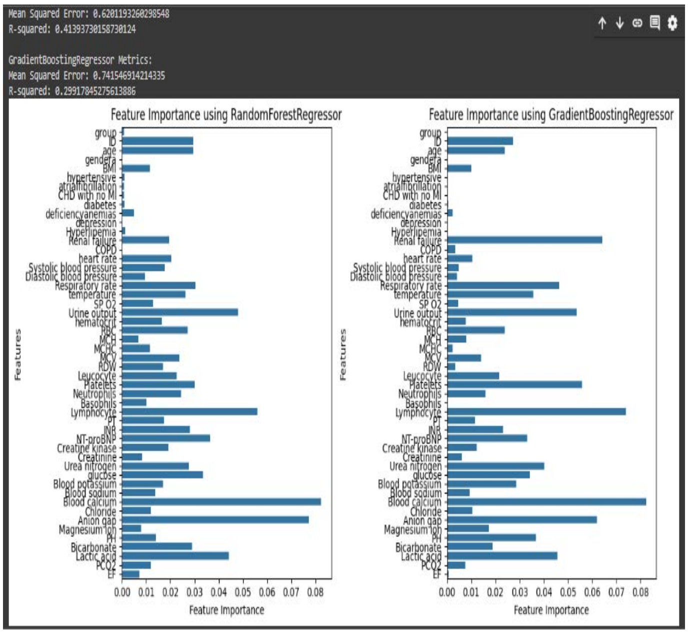

Figure 10: Model implementation and checking the impact on data ownership.

The investigation has been done with the use of ML models named RandomForestRegressor and GradientBoostRegressor. These models are responsible for shedding light on the potential effects of AI and patient data sovereignty in healthcare settings. The regression model's efficacy has been compared to deal with the predictive accuracy measures such as MSE and R squared value. As per the analysis, it has been determined that RandomForestRegressor is responsible for having lower MSE and higher R-squared value. On the other hand, this data also determines that RandomForestRegressor is comparatively better at predicting patient outcomes for predictive medical field analytics.

Moreover, the feature significance as can be determined from the above figure is responsible for providing details regarding the factors that have the most influence on the prediction process. This feature relevance is capable of highlighting a big impact on the predictive models such as demographics, medical problems and certain biomarkers. In such a scenario, AI becomes essential to prioritise various sorts of patient data. Understanding these intricacies becomes essential to managing the convergence of patient data governance and AI technology to promote a well-rounded strategy for upholding patient rights and legal frameworks.

Figure 11: Checking if the model is explaining its predictions.

The outcomes are influenced by the characteristics of the integration of SHAP. RandomForestRegressoris responsible for evaluating AI transparency in the forecasting of medical data, which ensures consistency with patient permission that further encourages responsibility. Moreover, SHAP is capable of improving the AI development process ethically through predictive healthcare analytics.

8. Discussion

The growing complexity of heavily data-driven and powered AI therapeutic technologies may someday challenge perceptions about personal accountability for medical results. In AI-driven and information-heavy health settings, systemic governance is going to be crucial in fostering congruence with stakeholder expectations in addition to consumer accountability.

Table 1: Model Performance.

Model	MSE	R-squared
RandomForeestRegressor	Lower	Higher
GradientBoostRegressor	Higher	Lower

The two models that have been utilised are responsible for outperforming the alternatives in terms of predicting the healthcare outcomes as seen by their higher r-squared value and lower MSE. These developments are responsible for highlighting AI's potential to improve patient care and medical decision-making by enabling more precise predictions based on different factors. In terms of ethics, the study highlights AI transparency with the use of SHAP(SHapleyAdditive exPlanations) to improve understanding through model prediction. Detailed clarifications linked to the variables impacting the outcomes not only increase predictive accuracy but also promote the development of ethical AI. The road ahead in the direction of focusing on patient data sovereignty and ethical artificial intelligence is difficult but exciting. The secret to improving healthcare is adopting the WHO's recommendations and making use of innovative technologies.

9. Conclusion

In a nutshell, this is notable that, the cooperation of medical experts, legislators, patients, and tech entrepreneurs will be essential in the future. In that aspect, this can use the promise of artificial intelligence and data sovereignty to create a healthcare environment that is inclusive, morally sound, and just as well as creative. The report has made proper recommendations that future research can concentrate further on dealing with the improvements of AI models for achieving more reliability. Dealing with the intricacies in making sure technological improvements further research is necessary to get more insights into governance solutions. Stakeholders are responsible for putting more focus on supporting innovation as well as moral integrity by proactively addressing these concerns.

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