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PATIENT-CARE: A ML Based Real-Time Decision Support System for Public Health, Integrating Epidemiological Modeling and Blockchain Technology

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Abstract

Background: Nowadays, public health structure is very much disrupted with intensive communicable diseases like dengue, malaria or covid-19 and non-communicable disease like cancer. Identifying proper segment of population susceptible to disease gives us an overall idea of the disease outbreak and helps in taking some precautionary measure form the governance point of view of the regulatory authority. Accordingly, there is always a substantial impact of different socio-demographic features in public health specifically for communicable diseases. **Materials & Method:** A Decision Support System (DSS) can help us tracking and monitoring, in real-time, the variation of segmented population in a certain geographic dimension about who are already infected or susceptible to infection. And further studying and analyzing and predicting different socio-demographic parameters creates certain impact in the pandemic scenario. On top of that applying machine learning technique helps us to plan or impose awareness rules and regulations. Epidemiological Model are effective in predicting population infection ratio, considering some parameters as constant. Furthermore, data privacy and security is always a major concern while dealing with sensitive data in Decision Support System. Not only that a decision support system should be able to accept data from diversified sources and can able to store that in decentralized manner adopting multiple stakeholders with different roles and responsibilities. We have proposed a DSS comprises of epidemiological model, machine learning technique, blockchain technology and anonymization technique. This novel Decision Support System will not only act as an alarming mechanism on varying population, geographic dimension and demographic factors but also will show the overall impact of those factors in any pandemic scenario keeping decentralization and security measure intact. **Conclusion:** The study effectively validates the effectiveness of the proposed model and substantiate that it surpasses different existing competitors' method as well.

Keywords: Epidemiological model; Feedback-based SIR Model; Public Health; Blockchain; Anonymization

1 Introduction

The emergence and re-emergence of infectious diseases poses significant challenges to global health, necessitating robust strategies for understanding and controlling their spread. Epidemiological models serve as critical tools in this endeavor, providing insights into the dynamics of disease transmission, informing public health interventions, and guiding policy decisions. These models range from simple deterministic frameworks to complex stochastic simulations, each offering unique advantages and addressing different aspects of disease dynamics. The 21st century has witnessed several notable outbreaks, including SARS, H1N1 influenza, Ebola, Zika, and most recently, COVID-19. Each of these events has underscored the importance of timely and accurate epidemiological modeling. By simulating the spread of pathogens, epidemiological models help to predict outbreak trajectories, to estimate the impact of interventions, and identify potential hotspots for targeted responses. Furthermore, they enable the assessment of various control strategies, such as vaccination, social distancing, and quarantine measures, thus aiding in the optimization of resource allocation and mitigation efforts. Blockchain technology outline a proper process to share information more conveniently without involving any third party. Blockchain is operating as a node or device that contains stored and encoded data permanently and acts as a decentralized database. It syncs latest blockchain data to fix all nodes constantly through a peer-to-peer network. Not only that, Sensitive information of the patients (PII) cannot be disclosed directly with other organizations or individuals as the demand and necessity of healthcare, but patients record always existed for Research and Development of new treatment of diseases.

In this paper, we present an advanced epidemiological model designed to enhance our understanding of infectious disease dynamics. Building upon the foundational Susceptible-Infectious-Recovered (SIR) framework, our model incorporates several critical extensions and also considered certain socio-economic elements. These additions allow for a more nuanced and realistic representation of disease spread, capturing the complexities observed in real-world scenarios. And to resolve the challenge of disclosing a patient data we anticipate and build a prototype system that share unidentified patient data through a decentralized platform. The platform increases the value of data through prevention of accessing any unnecessary information and filter and retain data before displaying to the users.

In the following sections, we first thoroughly study different state-of-the-art model and later deep drive into the technical aspects of the model. Later we show the analytical results of derived from the model. We also share the comparative analysis of the state of the art models and also describe how blockchain technology maintain decentralization and security aspect of the patient records. Our job concludes with a summary, a near-term forecast, and recommendations for further work.

2 Literature Survey

The balance of various factors within society significantly impacts public health, which includes the infrastructure dealing with communicable diseases. Over the past two decades, researchers have concentrated on developing mathematical models for communicable diseases to analyze their intensity and spread [1–5]. For instance, numerous studies have demonstrated that communicable diseases like cancer pose a substantial threat to public health [6,7].

Researchers have explored various genetic, environmental, behavioral, and socio-economic factors contributing to the cause of cancer, uncovering new areas for early diagnosis and suitable treatments [8]. Such studies also enable the analysis of risk patterns in large populations. Epidemiological models, such as the Susceptible-Infectious- Recovered (SIR) model, have been pivotal in understanding the effects of demographic and socio-economic factors on the spread of communicable diseases. These models highlight mitigation strategies that can flatten the curve of disease spread [9,10].

SIR model utilizes three tightly coupled differential equations to represent disease dynamics. Between 1927 and 1933, Kermack and McKendrick further advanced this model, which has since been instrumental in understanding infectious disease spread and evaluating control measures' potential impact on reducing disease intensity and mortality rates [2,11–13]. The COVID-19 pandemic has spurred numerous studies worldwide, including in India, where researchers have applied machine learning algorithms, neural networks, deep learning, and other time series forecasting algorithms to predict the disease's growth and analyze its spread [9,14,15]. Similarly, other communicable diseases, such as dengue, have also been studied using these advanced techniques [10]. The healthcare system increasingly relies on data-driven and information management systems to guide professionals in making informed decisions and improving services [16].

[17] Proposed a method for preserving data security and privacy at every stage of data transaction. [18] introduced a data-sharing platform based on consortium blockchain, ensuring decentralization and patient privacy through anonymization techniques for Personally Identifiable Information (PII). This approach facilitates knowledge sharing among stakeholders without compromising confidential information. Blockchain-based medical decision support systems have also been developed to ensure reliable and secure medical information management, focusing on areas like tissue donation, transplantation, and infertility treatment [17,19]. Named Entity Recognition (NER) using machine learning was introduced in 2015 with models like Hidden Markov Models and Conditional Random Field Models [20]. Deep learning advancements have since enhanced these models' efficiency. In 2021, anonymization of sensitive data was performed using Natural Language Processing (NLP) [21]. NLP processes unstructured data to identify and anonymize sensitive information. Other studies have used Large Language Models (LLMs) like BERT for NER on medical records, exploring anonymization possibilities [22]. A comparative study by [23] demonstrated that transformer-based models, particularly BERT, outperform non-transformer-based models in NER tasks [23].

3 Methodology

3.1 Data Source

Covid data collected from 20th April 2020 to 31st January 2022. Also, we have taken data that were published in the website of West Bengal Health and Family Welfare Department till 31st October 2022. We investigated covid related data collected from different boroughs of Kolkata in the said time span.

3.2 Workflow

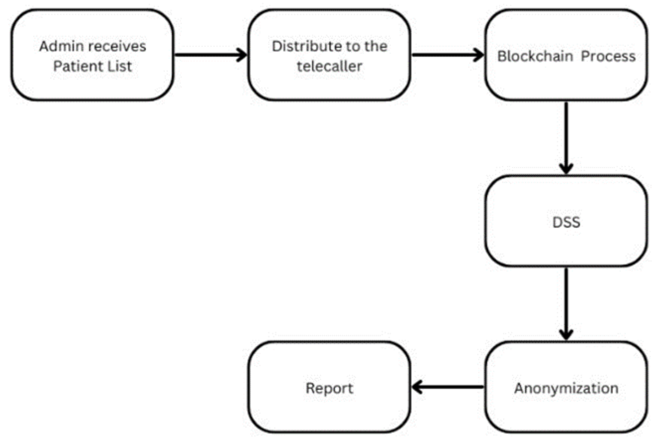

Fig 1. Workflow of Proposed DSS Model

Figure 1 shows the overall workflow of the proposed DSS model. The model describes that after receiving the patient dataset, it undergoes a random distribution process which distribute the dataset to the enlisted tele calling team members. The user authentication and further verification process is maintained in Blockchain to add the decentralization and security features. After modification or updation of medical records the data is inserted into the DSS which comprise of modified epidemiological model along with analytical and predictive features. Internal or external users can be able to view the reports after proper anonymization of the PII data. The end-to-end workflow happens in real-time.

3.3 Decision Support System

The DSS entails Epidemiological model and machine learning approach for predictive modelling.

3.3.1 Epidemiological Model

Epidemiological models are the better way of mathematically describing the intensity of communicable diseases. This type of model encapsulates the dynamics of communicable disease. The model divides the entire population into discrete segments. This classification is based on the status of the individual with respect to disease. SIR model is one of popular and mostly tested epidemiological model[9].

Susceptible (S) - The segment of population who are vulnerable to the disease.

Infected (I) - The population segment who are carrying the disease and have the potential to contaminate the disease.

Recovered or Resistant (R) - This is the group of population who have been infected and have recovered.

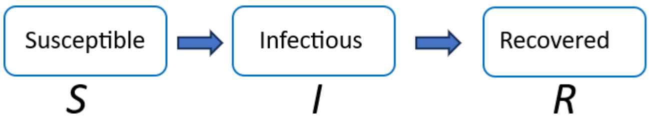

Fig 2. Conventional SIR Model

Based on SIR model (Figure 2), the rate of change of different segment of population is as follows:

$$\cdot \frac{ds}{dt} = -\alpha IS$$
$$\cdot \frac{dI}{dt} = \alpha IS - \beta I$$
$$\cdot \frac{dR}{dt} = \beta I$$

Where

N = S + I + R

α = Contamination rate

β = Recovery rate

With the following assumptions:

- Population is constant.
- Contact Ratio & Recovery rate is constant.
- After recovery no option for again been susceptible.

3.3.2 Feedback based SIR Model

Our study encompasses on reconsidering those assumption. We found that people were getting reinfected after recovering. A certain fraction of recovered population is entering to the "Susceptible" compartment directly from "Recovered" compartment. So, we proposed a feedback based SIR model (Figure 3) considering those fractions of population feeding back to the Susceptible population once again.

Feedback – based SIR Model For Communicable Diseases (CD): For CD, people after recovering from the disease tends to get reinfected-

- After 9 months of vaccination
- Immediately after vaccination
- Reinfection irrespective of vaccination of other precautionary measure.

So,

The modified susceptible population is

$$\frac{ds}{dt} = -rI\,(S_1 + S_2 + S_3 + S_4)$$

where

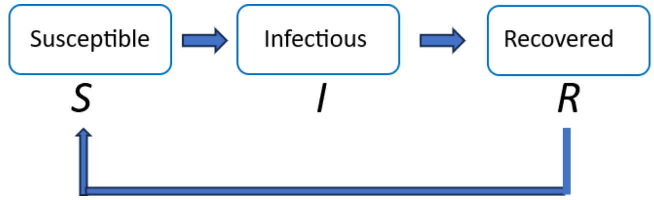

Fig 3. Feedback based SIR Model

'r' = rate of contract.

S_1 = Exposed Population yet to get infected

S_2 = 73% of the Population who are vaccinated 9 months prior (atleast 1 dose)

S_3 = 4.5% of the Population who can be reinfected immediately after vaccination.

S_4 = 5.94% of Recovered population.

This modified feedback model's accuracy model is 77 % more than the standard SIR model.

Feedback based SIR Model for Non-Communicable Disease (NCD): The stability and diversity of the SIR model can be extended to non-communicable diseases which also happens to be another major threat for public health. In recent days many studies have been conducted to implement mathematical analysis and epidemiological model to fit in non-communicable disease pattern[1]. NCD also has a tendency of recurrence. Quantifying the contribution of each factor is complex because it varies significantly based on the type of disease, individual patient characteristics, and other variables. However, research and clinical studies provide some insights into how various factors can influence recurrence rates. We have studied cancer as a NCD for identifying and quantifying the recurrence factors[24–26] and found that biological characteristics, initial treatment and genetic factors are the major contributing factors. But other factors such as individual lifestyle, patient's immune system, time since treatment and different socioeconomic factors also play a significant role in recurrence of non-communicable disease.

We extended the feedback based SIR Model for NCD adding fourth compartment as Recurrence (C). Along with the incident rate and recovery rate we have added recurrence rate (δ).

The recurrence rate (δ) can be modelled as a function of these factors:

δ = f (B, T, S E, S D)

where B indicate biological factors, T indicates treatment-related factors and SE as socio-economic factors, SD as socio-demographic factors. The modified SIR model with recurrence can be represented by the following set of differential equations:

$$\frac{dS}{dt} = -\beta S \frac{dI}{dt} = \beta S - \gamma I \frac{dR}{dt} = \gamma I - \delta R \frac{dC}{dt} = \delta R$$

3.3.3 Machine Learning Approach

Using the value of S, I and R, generated from the feedback-based SIR model, we extend out study to analyse temporal context for the variation of population segment and the implication or significance of the socio-demographic factors for both communicable and non-communicable disease (Figure 4). So, we have applied Auto-encoder, Count- based window, time-series clustering for training and k-NN for prediction.

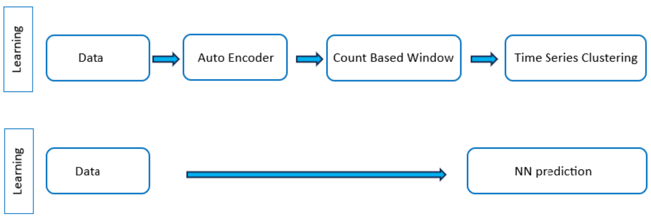

Fig 4. Proposed Machine Learning Model

3.4 Anonymization

It is important to fully mask the columns contains highly sensitive information along with partially masking of columns that contain both sensitive data and other information relevant for analysis and prediction, so we decided to use a multi - layer anonymizer. Figure 5 demonstrate the process where we first re-train a NER BERT model with our tabular dataset where sensitive features need to be fully masked and other features are partially masked based on the intensity of sensitivity of the data. This anonymizer is added to the DSS and used at the time of report extraction.

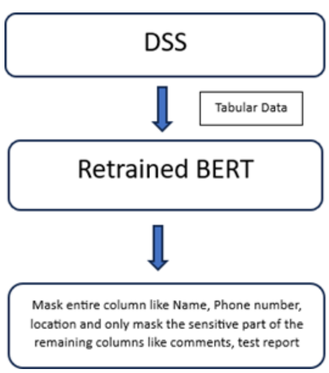

Fig 5. Anonymization Process Using Re-trained BERT Model

3.5 Blockchain

In the process of implementing PATIENT-CARE, we have used consortium blockchain which is based on consortium of different stakeholders each of which manages a node of the blockchain network. Few manager node, among the network of the organization will also be available to establish consortium consensus. The purpose of manager node is to track each transaction and from which node and the immediate broadcasted node. It will also help to implement the consensus protocol for the blockchain. Each organization node stores the data in its own transaction pool. Along with the manager node, the mined block is also broadcasted to other nodes of the network. Everyday a patient record is received from the concerned authority and that record is uploaded via a User Interface. These records are then randomly distributed to the tele calling team members. The retrieval process is based on searching the blockchain maintained by the consortium with search parameters like time interval, location, or patient id which is tagged before uploading the data into the system. This id is hashed to obscure patient identity. For retrieval process, users are categorised into intra - organizational (internal) and inter-organizational (external).

- **Identity & Access Management (IAM) with Blockchain for PATIENT-CARE**
  - **User Authentication**: Each time a user attempts to log in, their user ID and password are verified against the stored credentials in the blockchain. This process includes broadcasting the authentication request across the blockchain network, ensuring that all nodes participate in the verification.
  - **Blockchain Verification**: The results of the authentication process are recorded as a transaction on the blockchain. This ensures that every authentication attempt is documented, providing a clear and secure record of all access attempts.
  - **Unchangeable Auditable Pathway**: Blockchain technology maintains an unchangeable record of all transactions, assuring that each action is permanently documented and cannot be altered.
  - **Smart Contract**: Self-implementing contracts along with the terms of agreement directly written into code. They automatically implement and execute the identity processes based on predefined rules, ensuring efficiency and security.

By applying IAM with blockchain (Figure 6), we ensure a layer of security on top of decentralization.

- **System architecture of PATIENT-CARE system with Blockchain**

This specification is objected to architect, design and develop a secured and decentralized network for managing the health-related records for any Decision Support System. It is a decentralized network with a combination of multiple nodes that maintains a distributed ledger. Contributors to the network includes administrative persons, tele-callers,

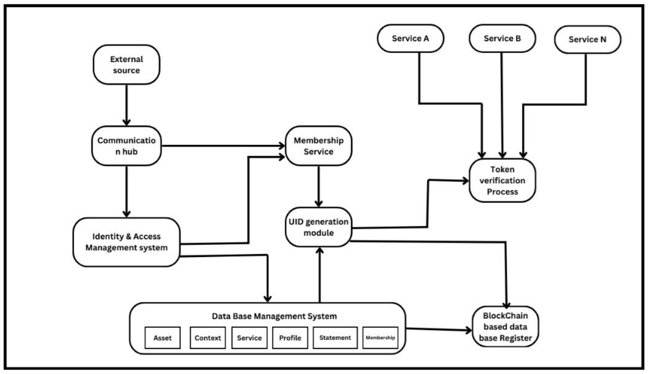

Fig 6. Identity and access management in Blockchain

healthcare stakeholders, researcher and other authorized entities mentioned in Figure 7. Key components collectively emphasize efficient administration, data processing, profile management, patient information control and summary contract handing that creates the core process of the system and lay down the overall infrastructure.

- **Register Administrator**: It manages user enrolment and authentication within the system. It accelerates the creation and maintenance of user accounts for stakeholders like healthcare providers, patients, administrators, and other authorized entities.
- **Service Provider Administration**: This manages healthcare service providers, such as clinics, hospitals, laboratories, and other medical facilities. It handles the registration and validation of healthcare providers within the system, enabling them to offer services, access authorized patient information, and interact with other platform components.
- **Profile management**: Profile Management oversees the maintenance and updating of user profiles. This com- ponent enables users to control their information and also ensuring data accuracy and completeness.
- **Summary Contract**: It is responsible for creating, managing, and enforcing summary contracts between various entities within the system. These contracts outline the terms, permissions, and obligations of patients, healthcare providers, and other stakeholders. Managing these contracts ensures that all interactions within the healthcare platform comply with predefined rules and agreements.
- **Unification and Compatibility:** Interoperability ensures smooth data flow and communication among various stakeholders. The system architecture emphasizes data security, user privacy, and efficient data exchange.
- **Flexibility and effectiveness**: The architecture is built to scale, handling an expanding user base and increasing volumes of health-related data. Strategies related to performance optimization are implemented to maintain a sensitive and efficient system.
- **Ongoing enhancement**: The system undergoes regular enhancements and updates to improve its features, performance and security and drawing on user guidance and technological progress.

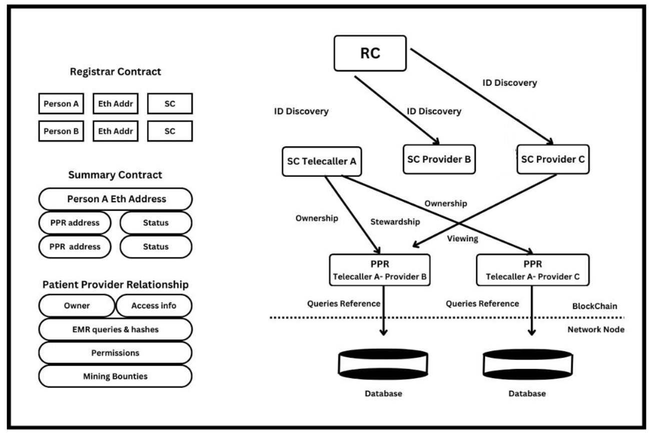

Fig 7. Blockchain with covid dataset

Figure 8 shows the step by step process for adding records in the Blockchain.

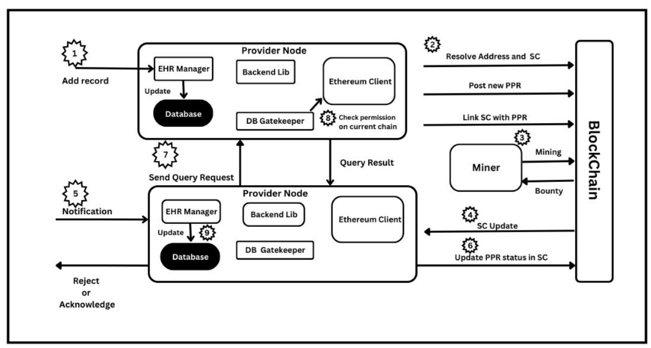

Fig 8. Steps to add a record

4 Results and Analysis

Figure 9helps to identify the spikes generated at different time intervals during the COVID-19 pandemic.

Table 1 represents a comparison of the overall accuracy level between the conventional SIR model and thefeedback-based SIR model.

In Figure 10 we show how feedback based SIR model outperforms the traditional SIR model when we plot the data derived from the each of the model along with the actual time series data. We found that the curve generated by the feedback

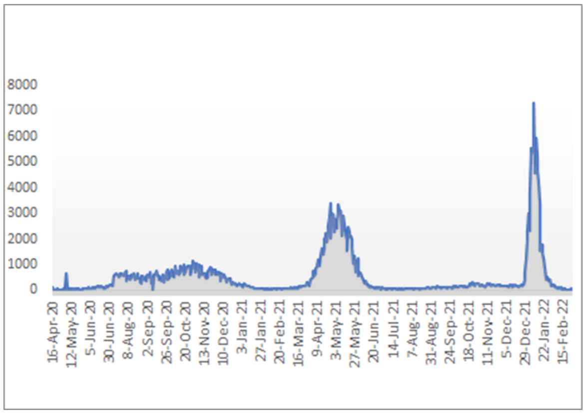

Fig 9. Spikes in different time frame of Disease (covid-19)

Table 1. Accuracy Standard SIR & Feedback SIR Model

Standard SIR Model	Feedback – based SIR Model
35%	62%

based SIR model is much nearer to the actual data curve compared to the curve generated by traditional SIR model.

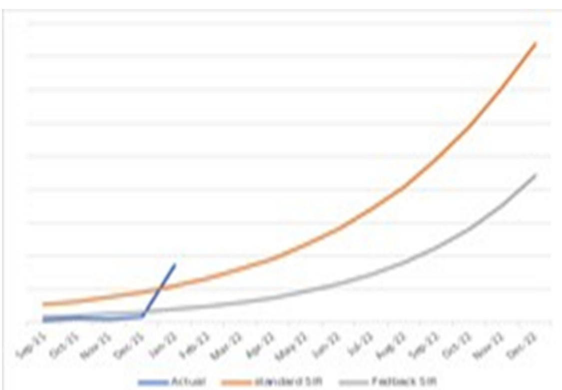

Fig 10. Comparison SIR Model & Feedback-based SIR Model

Table 2 shows the how the proposed ML model dominate the state of the art time series machine learning model.

Not only that, the proposed model is highly computationally efficient (Table 3) compared to that models.

Table 2. Comparison ML Model with other state-of-the art Model

Proposed ML Model	auto.arima	M5
93%	57%	43%

The anonymization technique, i.e., fine-tuned BERT model, that we follow in our overall Decision Support System ensures a high accuracy level. The comparison with the over techniques enlisted in Table 4.

Table 3. Computational Efficiency

Method	Training	Testing
Proposed ML Model	36 sec	< 1 sec
auto.arima	419 sec	3 sec
M5	1.44 sec	< 1 sec

Table 4. Comparison Anonymization technique with other state-of-the art technique

Evaluation Metrices	CRF	LSTM	BERT	Proposed Technique
F1-Score	0.75	0.82	0.88	**0.94**
Accuracy	0.80	0.87	0.93	**0.98**

The Figure 11 shows the overall correlation among the socio-economic and socio-demographic factors. Also, we found the correlation among the various variants that we experience during the pandemic time frame.

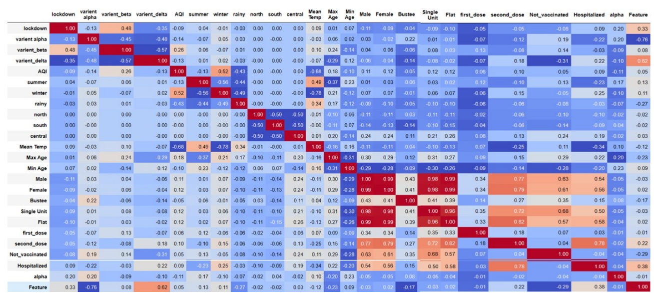

Fig 11. Co-relation of socio-demographic factors & their influence on the disease (covid-19)

From a survey conducted in sample population we find the following feedback for the DSS model.

Table 5. DSS Model Feedback from Survey

Metrix	Efficiency
Decision making accuracy	Doubled
Time and Effort	Half the time and at least 2 manpower reduced
Cost reduction	At least 20%
Increase of Satisfaction	85% of users reported higher satisfaction

Our proposed model not only give you an overall picture of current pandemic scenario related to communicable disease[27–29], it also provides a comprehensive view for both communicable and non-communicable disease, Our model also suggest about the influence of multiple socio-economic and socio-demographic factors not sticked to common factors like vaccination of population[28]. The proposed ML framework helps in predicting future pandemic taking into consideration of those different socio-economic and socio-demographic factors by maintaining an accuracy level of 93% compared to 85% in [28]. Like other study [30], we have also used a traditional epidemiological model. But we further modify that by adding feedback to that which approximately doubled the efficiency level compared to the traditional one. As we may face multiple stakeholders, we decentralized the overall data storage and retrieval phase using Blockchain which is still now only used in sharing specific Electronic Health Records [30]. On top of that as we are dealing with highly sensitive data, we used an additional anonymization technique for protecting those PII data.

5 Conclusion & Future Work

To combat communicable and non-communicable diseases like COVID-19 and cancer, we need to be more organized and effective in both medical and technological perspectives. The threat posed by epidemiological circumstances to public health can be mitigated with proper analysis and prediction. Data analysis and prediction will aid authorities and public health personnel in situation evaluation and decision-making. The SIR model is one of the most broadly used epidemiological models in public health. We have aimed to address certain limitations of the conventional SIR model and refine it to increase its efficiency. By comparing real data with both the conventional and our modified SIR model, we demonstrate that the modified model has superior predictive efficiency. Our innovation extends to evaluating the influence of various impulsive factors associated with public health in real-time and how those factors are correlated with each other. The ML model that we used is also computationally more efficient com- pared to state-of-the-art approach. For anonymization and security of sensitive data like health records, we have used Blockchain Technology. This also helps in sharing reports in a secured and decentralized way.

We have accounted for virus reinfection or reaction to improve the accuracy of forecasting and prediction. Our data and other calculation factors are based on a specific locality. In future, our planning is to expand our model to more global aspects with additional decisive parameters. We will also enhance the anonymization efforts for unstructured data, such as image data and textual documents. The data search and retrieval techniques used in the blockchain can be fine-tuned to increase the model's efficiency.

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