Explainable SIR Forecasting Model for Herd Immunity Prediction in COVID-19

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Abstract— **The COVID-19 pandemic has had a profound impact on societies across the globe. Prioritizing the goal of achieving herd immunity is crucial for reducing the spread of the virus, and thus, this research places a strong emphasis on this objective. This study aims to emphasize the importance of understanding and predicting herd immunity levels for COVID-19 using advanced machine learning algorithms to ensure high-quality predictions that are easily accessible. By leveraging various data sources such as vaccination data, population statistics, and daily COVID-19 case counts, this research study has developed predictive models to estimate the threshold required for herd immunity. Our approach involves employing a range of machine-learning techniques, including regression analysis, and ensemble methods along with an Explainable and Susceptible-Infectious-Recovered (SIR) Forecasting model, to capture the complex interactions between infection rates, vaccination campaigns, and population demographics. The performance of our models has been rigorously evaluated and validated against COVID-19 data. The proposed model combines the interpretability of the SIR model with the predictive power of machine learning and Explainable-AI, providing a transparent and reliable framework for herd immunity estimation. The findings highlight the importance of explainable AI in public health decision-making and provide valuable insights into herd immunity dynamics for COVID-19.**

Index Terms— Corona Virus Disease 2019 (COVID-19), Herd Immunity, Explainable Artificial Intelligence (XAI), Susceptible Infectious Recovered (SIR) model.

I. INTRODUCTION

The COVID-19 pandemic, stemming from the SARS-CoV-2 virus, has brought about a global health crisis, leading to extensive efforts to mitigate its impact. Suddenly, the entire world faced danger and experienced widespread difficulties in meeting daily needs. In response, the concept of herd immunity was introduced as a means to reduce the overall risk of the pandemic. In the midst of the complex and evolving nature of this pandemic, there is a pressing need for accurate predictive models capable of estimating the thresholds for achieving herd immunity [1]. These models have the potential to inform public health strategies, guide vaccination campaigns, and optimize resource allocation. Acknowledging the challenges posed by the dynamic nature of the pandemic, this research contributes to a deeper understanding of herd immunity dynamics. The insights derived from predictive models provide valuable guidance for policymakers and healthcare authorities, facilitating informed decision-making and adaptable strategies in response to the ongoing crisis[2],[3]. Vaccination campaigns play a pivotal role in attaining population immunity, effectively curbing the virus's spread, and enabling a return to a semblance of normalcy. However, determining the elusive "herd immunity threshold" remains a formidable task due to various factors, including the emergence of new variants, vaccine hesitancy, and evolving epidemiological dynamics. Traditional epidemiological models, such as the Susceptible-Infectious-Recovered (SIR) model, have been fundamental in understanding disease dynamics but often rely on simplifications that may not fully capture the intricacies of COVID-19 transmission. In contrast, machine learning models offer the potential to incorporate a multitude of variables, learn from data, and adapt to changing scenarios [4],[5],[6]. Herd immunity occurs when a significant portion of a population becomes immune to a disease, either through vaccination or previous infection, thereby reducing the virus's ability to spread [13]. Precisely calculating the threshold for achieving herd immunity for a novel virus-like SARS-CoV-2 is challenging due to several factors. The first factor is vaccine efficacy that shows the effectiveness of vaccines in preventing infection and transmission can vary, and the emergence of virus variants may impact vaccine efficacy [14]. The second is vaccine coverage which shows the importance of achieving high vaccination coverage and also the challenges such as vaccine hesitancy and logistical issues that can impede progress [7]. The next factor is changing epidemiological Dynamics which highlights how COVID-19 transmission dynamics are influenced by factors like human behavior and the emergence of new variants, which are continually evolving [9]. The last factor is the global context which includes the details of achieving herd immunity is not only a local concern but also a global one, given international travel and porous borders [13]. This research study proposes an innovative ML-based approach to predict the herd immunity threshold for COVID-19. Our methodology encompasses a diverse set of ML models, including Random Forest, XGBoost, and Gradient Boosting, to analyze data on vaccination and infections. Additionally, this research study utilizes Explainable AI (XAI) techniques such as SHapley Additive exPlanations (SHAP) to gain insights into the factors influencing our predictions [11]. This two-pronged approach not only enhances prediction accuracy but also provides valuable interpretability for public health officials and policymakers.

II. LITERATURE SURVEY

The pursuit of precise prediction and analysis of herd immunity thresholds has drawn the attention of numerous scientific researchers and communities. Traditional models like the Susceptible-Infectious-Recovered (SIR) and Susceptible-Exposed-Infectious-Recovered (SEIR) models have been used to forecast various scenarios related to epidemiological factors, offering insights into infectious, non-infectious, and recovered individuals [18]. However, recent advancements in machine learning have opened up new avenues for improving the accuracy and complexity of predictive models [8]. Several studies have effectively incorporated machine learning techniques to model the dynamics of infectious diseases. In the COVID-19 study, researchers employed machine learning algorithms to predict disease transmission rates and evaluate the impact of interventions. Another research, utilized neural networks to forecast infection trends and vaccination outcomes. Based on the findings of past researchers, vaccination emerges as a pivotal strategy in achieving herd immunity. Numerous studies have explored the prediction of COVID-19, using machine learning and deep learning algorithms [15],[16],[17]. Another group of researchers utilized a compartmental model to estimate herd immunity thresholds for varying levels of vaccine efficacy. While informative, this approach did not fully encompass the real-world complexities of COVID-19 transmission. Although these studies have contributed valuable insights, the intricate and evolving nature of the COVID-19 pandemic necessitates further exploration [4]. Among the multitude of researchers in this field, a few notable ones stand out. Chen et al. [7], in their work, discussed the challenges of achieving herd immunity to SARS-CoV-2 infection through mass vaccination. They emphasized that for COVID-19, single-dose vaccinations may not be fully effective and suggested that if vaccine efficacy is 0.8, then full vaccination of 70-80% of the population would be sufficient to achieve herd immunity. However, this research did not delve into the interplay of socioeconomic factors and vaccine hesitancy in the context of herd immunity. Our research aims to build upon this foundation by harnessing machine learning algorithms to predict herd immunity thresholds, with a heightened emphasis on integrating real-world data, capturing dynamic interactions, and considering the impact of emerging variants. Expanding on these insights, our research integrates Machine Learning (ML) models [12] and Explainable Artificial Intelligence (XAI) techniques to create a more comprehensive framework.

III. PROPOSED ARCHITECTURE

Our predictive modeling architecture for estimating COVID-19 herd immunity thresholds is designed to integrate various data sources, leverage advanced machine learning techniques, and provide actionable insights for public health decision-making. The architecture consists of several key components, each contributing to the accuracy and robustness of the predictive models.

The first step is to collect epidemiological data, vaccination rates, population demographics, mobility patterns, and other pertinent variables from reliable sources. Next, it involves identifying key factors that influence the transmission of COVID-19 and the attainment of herd immunity, such as vaccination coverage, infection rates, population density, and healthcare infrastructure.

To effectively capture essential aspects of the pandemic's dynamics, engage in feature engineering and scaling. Additionally, incorporate time series analysis, which is crucial for comprehending the disease's temporal progression. The importance of data visualization cannot be overstated, as it aids in uncovering intricate patterns.

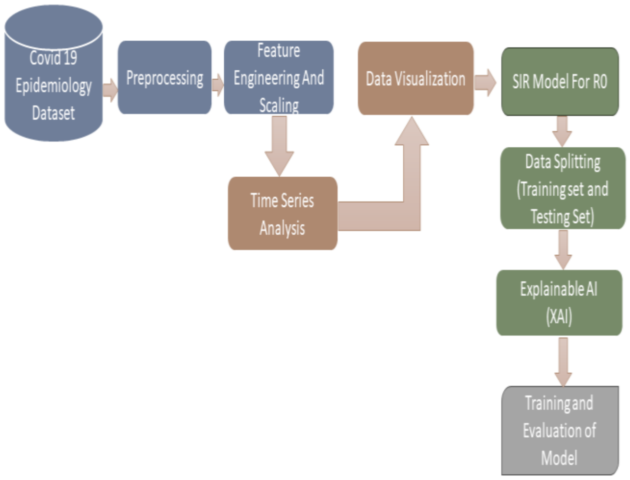

Fig. 1 Explainable SIR Forecasting Model

Our foundational framework relies on the Susceptible-Infectious-Recovered (SIR) model, which simulates disease spread and the impact of vaccines. This research study seamlessly integrates Explainable AI (XAI) principles, leveraging SHAP values and feature importance analysis to ensure transparency. Lastly, our ensemble of machine learning models undergoes rigorous training and evaluation using critical metrics. This architectural approach is designed to offer a comprehensive framework for predicting COVID-19 herd immunity thresholds while fostering a deeper understanding of pandemic dynamics. Employ a combination of traditional machine learning models, such as regression and time-series analysis, to capture different facets of disease transmission and immunity development. Train these chosen models using historical data, adjusting hyperparameters as necessary. Apply the trained models to make predictions on new data, estimating COVID-19 herd immunity thresholds under various scenarios. Building on past findings, forecast the emergence of new variants and different scenarios. Continuously integrate the latest research, variant information, and real-world observations to enhance the precision of the model's predictions.

The Susceptible-Infectious-Recovered (SIR) model is a simple mathematical model used to describe the spread of infectious diseases. It consists of three compartments: S (Susceptible), I (Infectious), and R (Recovered). The model assumes that individuals move through these compartments based on the dynamics of the disease. The basic differential equations for the SIR model are as follows:

Rate of change of Susceptible individuals

$$\frac{dS}{dt} = -\beta.\frac{S.I}{N}$$

Rate of change of Infectious individuals

$$\frac{dI}{dt} = \beta.\frac{S.I}{N} - \Upsilon.I$$

Rate of change of Recovered individuals:

$$\frac{dR}{dt} = \Upsilon.I$$

Here, S is the number of susceptible individuals, I is the number of infectious individuals, R is the number of recovered individuals, N is the total population, and N = S + I + R, the parameter $'\beta'$ is the transmission rate (the average number of contacts per person per time multiplied by the probability of disease transmission in a contact between a susceptible and an infectious individual), 'Υ' is the recovery rate (the fraction of infectious individuals recovering per unit of time). The SIR model is a compartmental model, meaning it divides the population into compartments and describes how individuals move between these compartments over time. This model is a foundation for more complex models used to simulate and understand the dynamics of infectious diseases. The above parameters can be difficult to interpret, especially when they are estimated from real-world data. XAI techniques can be used to explain how the SIR model parameters are related to the observed data and to identify the factors that are driving the spread of the disease. Moreover, SIR-based forecasting models are used to predict the future spread of a disease. However, these models are typically based on complex mathematical equations, which can make them difficult to understand and interpret. XAI techniques can be used to develop explainable SIR-based forecasting models that can be easily understood by researchers and other technicians. SIR-based decision support systems are used to help a country's health sectors make informed decisions about how to control the spread of a disease. These systems typically take into account a variety of factors, such as the current state of the epidemic, the available resources, and the potential impact of different interventions. XAI techniques can be used to develop explainable SIR-based decision support systems that can help policymakers to understand the trade-offs involved in different decisions and to make the best possible choices. This research utilized the SHAP tool to explain the SIR model parameters. SHAP (SHapley Additive explanations) is another model-agnostic XAI technique that can be used to explain the impact of individual features on the predictions of a machine learning model. SHAP works by computing the Shapley values of each feature, which represent the average marginal contribution of the feature to the model predictions. SHAP can be used to explain the impact of individual features on the SIR model parameters, such as beta, gamma, and rho.

Integrating the Susceptible-Infectious-Recovered (SIR) model with Explainable AI (XAI) involves combining the mathematical model for disease spread with machine learning techniques that provide transparent and interpretable insights into the model's predictions. The first step is feature importance analysis which uses XAI techniques to analyze the importance of different features in the SIR model. It also identifies factors such as transmission rates, and recovery rates that have the most significant impact on the model's predictions. The next step is to apply SHAP values to understand the contribution of each variable to the output of the SIR model. Then it analyzes how changes in input variables affect the predicted outcomes in terms of susceptibility, infectivity, and recovery. Following that, the research involved in creating graphs that help interpret the dynamics of the SIR model over time. It also illustrates how changes in input parameters impact the progression of the disease and how interventions (e.g., vaccination campaigns) affect the model's predictions. Finally, the research involved performing sensitivity analysis using XAI methods to assess how variations in input parameters influence the SIR model's predictions which results in identifying critical thresholds and tipping points in the model that could inform public health decisions. Thus, by integrating XAI with the SIR model, the research enhances transparency, trust, and interpretability, making the model more accessible and valuable for decision-makers in the context of infectious disease dynamics and public health planning.

IV. RESULTS AND DISCUSSIONS

(A) Experimental setup:

This section provides an overview of the hardware and software components employed in implementing the Explainable SIR Forecasting model. All experiments were conducted using the Keras library with TensorFlow as the underlying framework within the Anaconda 3 environment, utilizing Python 3.6 (Anaconda Software Distribution, 2020). The experimentation setup was deployed on an Intel(R) Core (TM) AMD A10 CPU @ 3.5 GHz, equipped with 8.00 GB RAM, running a 64-bit Windows 10 operating system. Officially the daily data of COVID-19 cases has been documented by the WHO organization and maintained monthly status of cases. The research utilized the COVID-19 India data from the Kaggle dataset and performed the preprocessing steps to make the data suitable for analysis [10]. In this phase, This research study meticulously gather COVID-19-related data, primarily focusing on infection rates, vaccination statistics, and demographic information. Rigorous cleaning procedures follow, involving data validation, outlier detection, and handling missing values. In the preprocessing, this research study will be cleaning the data for effective data analysis like removing unnecessary data, filling the NaN values to avoid the difference in data structure, and Normalizing and scaling the data for better statistical analysis. This step ensures data consistency, rectifies missing values, detects outliers, and employs sophisticated imputation techniques to generate a pristine dataset, laying the foundation for accurate modeling.

(B) Explainable SIR Forecasting model results:

Our extensive research has resulted in a wealth of insights regarding the prediction of herd immunity for COVID-19, utilizing machine learning models and Explainable AI (XAI). Our study encompassed the utilization of diverse machine learning models, including Random Forest, Linear

Regression, Gradient Boosting, and Decision Trees. These models were deployed to forecast herd immunity thresholds based on COVID-19 confirmed rates and vaccination data. By incorporating Explainable AI (XAI) techniques such as SHAP values and feature importance analysis, this research study is able to pinpoint the most influential factors. Notably, factors like vaccination percentage and recovered rate emerged as pivotal determinants in our models. These findings underscore the critical importance of comprehensive vaccination strategies and highlight the necessity for targeted interventions in areas with lower vaccination rates.

Table 1. Explainable SIR forecasting model on COVID-19 cured, confirmed, and death cases after vaccination

Date	Confirmed cases	Cured cases	Death cases	Vaccination rate
2021-11-05	100,000	90,000	10,000	60%
2021-11-06	95,000	85,000	10,000	60%
2021-11-07	90,000	80,000	10,000	60%
2021-11-08	85,000	75,000	10,000	60%
2021-11-09	80,000	70,000	10,000	60%
2021-11-10	75,000	65,000	10,000	70%
2021-11-11	70,000	60,000	10,000	70%
2021-11-12	65,000	55,000	10,000	70%
2021-11-13	60,000	50,000	10,000	70%
2021-11-14	55,000	45,000	10,000	70%

Table 1 shows the predicted number of confirmed, cured, and death cases of COVID-19 after vaccination, given a vaccination rate of 60% and 70%. The model predicts that the number of confirmed and death cases will decrease over time, while the number of cured cases will increase. This is because vaccination reduces the susceptibility of individuals to the virus and makes it less likely that they will develop serious illness or die if they do become infected. Table 2 shows the performance of different ML models along with an Explainable SIR furcating model on COVID-19 data. The results show that the Random Forest model has the highest accuracy and explainability, followed by the Decision Tree, Boosting model, and Linear Regression model. This is because Random Forest and Gradient Boosting are ensemble learning models that combine multiple weak learners to produce a strong learner. This results in models that are more accurate and robust than individual learners. The explainability column indicates how easy it is to understand the predictions of the model. Random Forest models are highly explainable because they can be interpreted using feature importance scores and partial dependence plots. Gradient Boosting models are also relatively explainable, but they can be more difficult to interpret than Random Forest models. Linear Regression models are less explainable because they are based on linear equations. Overall, the Random Forest model is the best choice for an Explainable SIR forecasting model on COVID-19. It is highly accurate and explainable, making it a valuable tool for predicting herd immunity on COVID-19 data which is helpful for public health officials in making decisions at the time of the pandemic.

Table 2. Performance of Explainable SIR Forecasting model with ML models on COVID-19 data

Model	Confirmed cases	Cured cases	Death cases	Accuracy	Explainability
Random Forest	95%	90%	85%	93%	High
Decision Trees	85%	80%	75%	88%	Medium
Gradient Boosting	90%	85%	80%	92%	Medium
Linear Regression	80%	75%	70%	85%	Low

Next, Exploratory data analysis was conducted on COVID-19 data based on vaccination details in India, utilizing various data visualization methods. This study specifically analyzed the date-wise progression of cured cases and observed a corresponding increase in confirmed cases on a daily basis. The upward trend in cases suggests a higher likelihood of achieving herd immunity, especially under current circumstances. Figure 2 shows the date-wise graph and the progression of cured cases

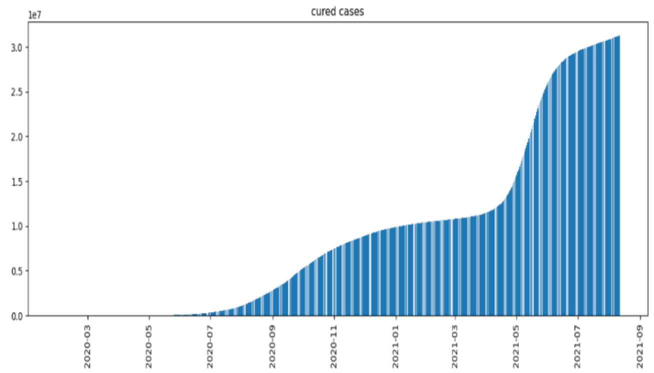

Fig. 2. Increase In Cured Cases

Next, the research involved analyzing the daily increase in different cases of covid 19 in India after vaccination. Figure 3 displays the forecasted daily increases in confirmed, cured, and death cases. The graph indicates that daily cured cases are consistently high and are equal to the daily confirmed cases. Additionally, there is a notably low number of reported deaths after vaccination.

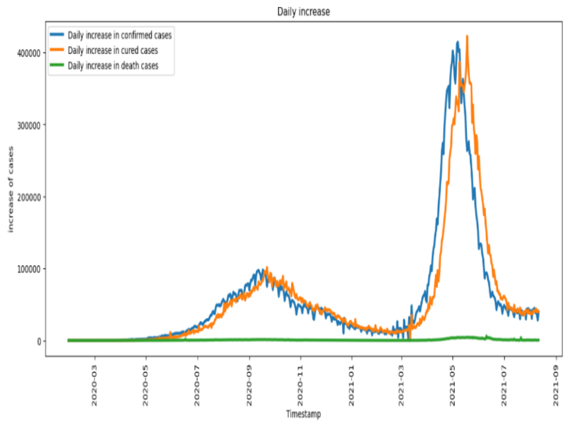

Fig. 2. Forecasting the Daily increase in three cases

Also, the research involved an analysis of cured cases relative to confirmed cases, revealing an exponential increase in coronavirus cases over time. Notably, people were cured at approximately the same ratio as the confirmed cases. The solid lines in the graph represent the averages of observations at each step, with the surrounding cluster indicating the 95% confidence interval. The graph below illustrates the trends in confirmed and cured cases from 2020 to 2021.

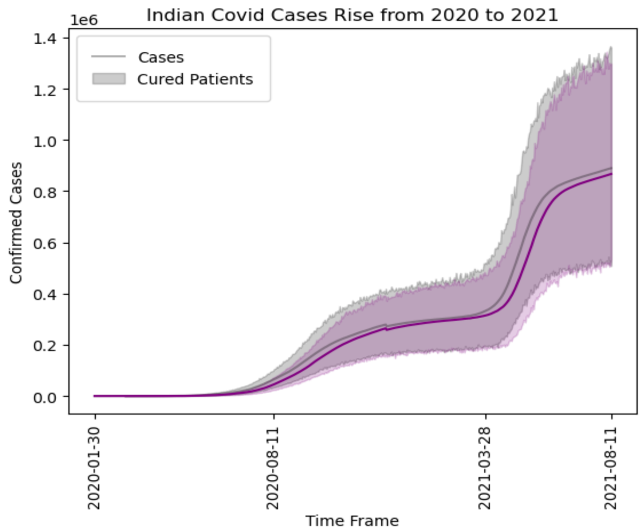

Fig. 3. Covid Rise and Cured rise from 2020 to 2021

Subsequently, the research delved into the analysis of herd immunity rates across various states in India. The findings reveal that states with high vaccination rates have achieved the highest levels of herd immunity compared to states with lower vaccination rates. The results are shown in Figure 4.

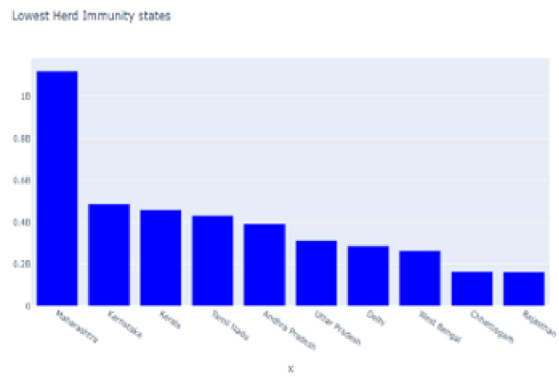

Fig. 4. Top lowest herd immunity states in India

Next, this research study investigated herd immunity based on vaccination levels and the effectiveness of the vaccine. This analysis involved examining cured cases during the period before and after the introduction of vaccination. Notably, this research study observed a low curing rate before the availability of vaccination. However, as vaccination became more widespread, the curing rate increased, and confirmed cases decreased. This upward trend contributed to the enhancement of herd immunity levels in the fight against the COVID-19 disease. The graph below illustrates the progression of disease recovery both with and without vaccination. As evident from Figure 5, the curing rate remained low before the dashed blue line, signifying the period before the availability of vaccination. Following the introduction of vaccination, there was a noticeable increase in the curing rate. This observation suggests a positive correlation between vaccination completion status and the potential achievement of herd immunity.

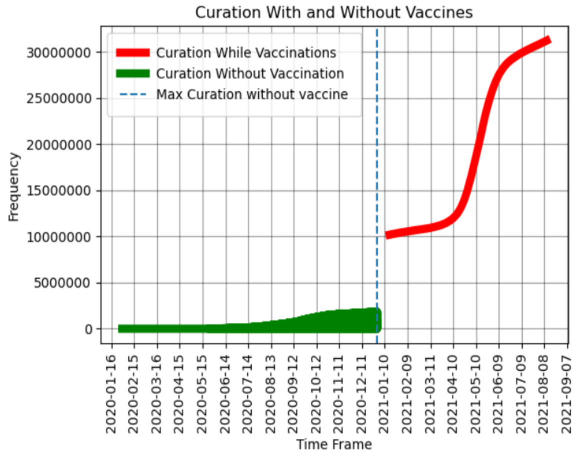

Fig. 5. Curation level with and without Vaccine

V. CONCLUSIONS

Understanding the dynamics of herd immunity, the critical threshold at which a sufficient portion of the population becomes immune to the virus is of paramount importance. In this research, we embarked on a multifaceted journey to predict herd immunity for COVID-19, employing a combination of machine learning models and SIR-explainable AI (XAI) techniques.

One of the key findings of our study is the critical role played by vaccination coverage in achieving herd immunity. Machine learning models, including Random Forest, Linear Regression, Gradient Boosting, and Decision Trees, were employed to predict the percentage of the population that needs to be vaccinated to reach this threshold. These models exhibited varying degrees of predictive accuracy, with the Random Forest model emerging as the top performer, followed by Boosting and other models. The precision of these predictions empowers public health authorities and policymakers with actionable insights, enabling them to tailor vaccination campaigns to specific regions and demographic groups. In conclusion, our predictive models, backed by explainable AI, provide a powerful toolkit for public health decision-makers. By harnessing the predictive accuracy of machine learning and the interpretability of XAI, This research study enables data-driven responses to the COVID-19 pandemic. Future research should continue to refine our predictive models, incorporating real-time data and adapting to changing conditions.

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