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Research Article

Explainable Machine Learning on Health Management Information System Data to Unveil Health Factors Affecting Maternal Mortality Ratio of Districts in India towards Achieving Sustainable Development Goals

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ABSTRACT

Purpose: Maternal mortality remained to persist in many developing countries. India being the most populous developing country has several cultural differences and beliefs on health systems and may have disparities in receiving proper maternal health care. High data availability and under-utilization of data centric decision making is a key reason for ineffective performance of health systems. Enacting machine learning on such data to aid in sub-divisional policy formulation to address area level problems will eradicate major disparities in recipients of health services.

Methods: Glass box machine learning models are trained on the data to obtain importance of features in defining the maternal mortality of a district. Furthermore, black box machine learning models are trained with hyper-parameter tuning and best model is chosen to perform explainable machine learning to generate explanations for each district prediction. A hybrid explainable machine learning approach is proposed on black-box machine learning models where Shapley Additive Explanation and Local Interpretable Model-agnostic Explanations are combined to generate final explanations.

Results: There may be several differences even among nearby districts. Health Management Information System data is analyzed with help of Machine Learning techniques and Explainable Machine Learning techniques are used on the trained models to evaluate the contributing factors for each district.

Conclusion: The factors that are specific to each district can help in formulating region specific health policies that minimize the disparities of progress of preventing maternal mortality over the districts of India. The paper has highlighted the advantages of using explainable machine learning in extracting complicated patterns of the data.

Keywords: Maternal Mortality, Sustainable Development Goals, Health Governance, Explainable Machine Learning

INTRODUCTION

During the 1900s, the maternal mortality ratio of countries remained at very high rates and from the year 1937, these rates began to decline gradually. This decline observed is mainly due to the improvement in maternal care offered by the birth attendants. In addition, few other factors such as poverty and lack of nutrition have played a minor role in determining maternal mortality ratios. Even in the developing countries, several maternal deaths occurred due to improper medical facilities and lack of maternal care provided to the pregnant women [1].

With gradual development of the countries, the mortality rates of the respective countries also change. The maternal mortality ratio has started to become a prominent indicator to measure the progress of development of the country [2]. With the implementation of millennium development goals, one of the relevant goals (Millennium Development Goal 5) which focussed on the improvement of health in the countries has been an important target for every developing country. Entire world has recognised the importance of eradicating maternal mortality which is a preventable issue. The reasons for high maternal mortality in developing nations is majorly due to the lack of effective medical services, lack of knowledge and literacy, etc. As on the year 2000, the estimated number of maternal deaths occurring in the entire world is 529000 [3]. Six developing countries that include India has accounted for more than 50 % of the maternal deaths occurred during the year 2008. Compared to Indonesia, which has lower maternal mortality ratio in the beginning, India has improved better in terms of skilled medical personal attended births, etc., and had seen higher decline in the maternal mortality ratio than Indonesia [4].

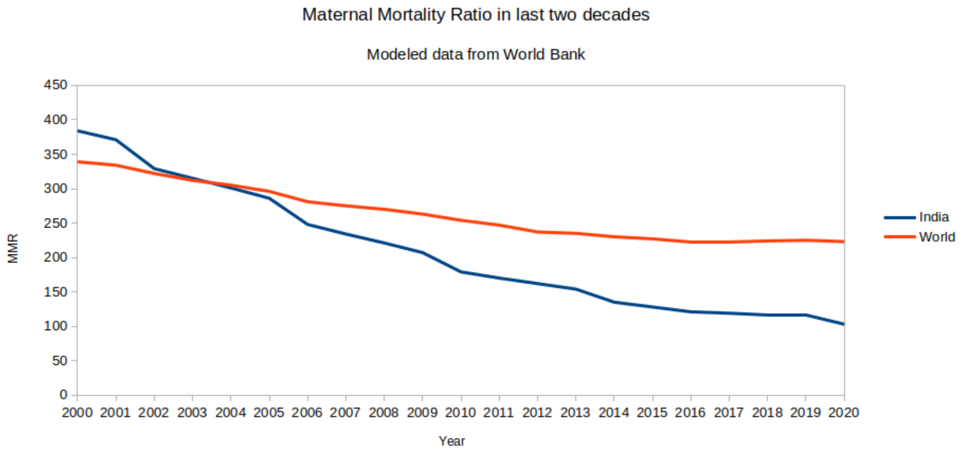

Figure 1 Maternal Mortality Ratio for last two decades

Learning from Millennium Development Goals, a substantial growth and developments in health systems and their performance is essential for achieving better progress [5]. Efforts of several countries are focused on improving maternal and child health which has led to greater emphasis of countries towards health goals rather than focusing on other development factors [6]. Following the partial success of the Millennium Development Goals in several developing countries, the United Nations has agreed to meet new targets which are collectively defined as the Sustainable Development Goals in the year 2015 [7]. The Sustainable Development Goals are applicable to all the countries and the countries should meet targets listed under Sustainable Development Goals by the year 2030 [8]. An important goal among the 17 goals is Goal 3: Good Health and Well-being, which consists of 13 important targets which every country must meet to ensure sustainability in the world. Eradication of maternal mortality is one of the key targets, which corresponds to reducing maternal deaths which are preventable with a little emphasis [8]. To achieve the sustainable development goals, countries need to put more effort and focus on the problems at root level. It is evident that to control a nation's maternal mortality, it is extremely important for the national level policies to formulate sub divisional policies which are dealing with specific issues of a region to ensure effective control of maternal mortality. Countries can even make use of data science and artificial intelligence to properly measure the progress and allocate the resources effectively to achieve the defined targets of the sustainable development goals [9].

India, with a population of around 1.4 billion, is a lower-middle income country but performing exceptionally in preventing maternal mortality in the overall country. Compared to the world's maternal mortality ratio for the last two decades, India is performing better than ever in bringing down the maternal mortality ratio (Figure 1). With National Health Mission's extensive priority towards reducing maternal and newborn mortality, overall progress of the maternal mortality ratio in India is on track with the sustainable development goals with the current estimated projections. But the disruptions caused due to Corona Virus Disease (COVID-19) may have an impact on the progress of the sustainable development goals which may lead to deviation from the track of achieving success in terms of reduction of maternal mortality [10].

Though the progress of country is moving fine at the national level, the maternal mortality ratio of individual states has shown several disparities due to various undetermined reasons. State wise the maternal mortality ratio of Indian states explains us that most of the north east Indian states have higher the maternal mortality ratio compared to that of southern India. Major mortality cases are caused by haemorrhage, especially in Empowered Action Group states [11]. Areas with lack of women literacy, and availability of proper medical practicioners need to be looked after with proper measures and initiatives to bring down maternal mortality [12]. Also, it is essential to devise and implement appropriate solutions based on the different predominant causes of the respective states. Looking into reduction of maternal mortality as a subregional problem would address the issue with more precise solutions which help the country to achieve nearly zero the maternal mortality ratio [11].

There are several researches performed to study and analyze the situation of maternal mortality in many areas both at micro and macro level. It is a notable fact that applications of Machine Learning exist widely in the scope of health care industry and has major contribution in levelling up the health care delivery. Future medical practitioners will be inculcating machine learning tools with their health care services to figure out novel strategies and unveiling key facts that might take the medical industry to its peak. Researchers have made use of data analysis, image recognition, etc., to solve many problems that existing medical professionals are unable to do with conventional practices [13].

But machine learning cannot be generalized on a dataset and simply expected to work fine. There exist several contextual differences in the cases where machine learning models could go wrong. Hence, careful selection and narrowing down of focus on machine learning models is required. Such mindful filtering of machine learning training process will enhance the results of machine learning models and helps in using machine learning to benefit patients and medical professionals [14]. Yet there is a concern towards the ethical point of view in applying machine learning in the areas of health care [13]. Many researchers have applied machine learning on maternal mortality data using models like Classification and Regression Trees, Artificial Neural Networks, Support Vector Machine, Random Forests, etc., and have succeeded in obtaining useful insights through the models.

[15] has published their work on predicting exclusive breastfeeding using machine learning which successfully explored non-linear relationships among the data related to post-partum factors in maternity ward. They have successfully trained several machine learning models and listed the best models, using them for explainable machine learning. [16] have worked on applying machine learning and explainable machine learning to explore risk factors that can determine based on which in-hospital mortality due to sepsis occurs. COVID - 19 has increasingly prompted the world's best researchers to start working on complex analytical research in health care sector which has led to a rise in application of machine learning in solving various health sector problems. [17] has worked on COVID - 19 mortality rate analysis using machine learning and hyper parameter tuning techniques.

It is evident that the quality of electronic health records data impacts the performance of predictive models and accuracy of information learned from the models [18]. Boosting models have also turned out to be showing better predictive performance on maternal mortality datasets [19]. [20] have worked on novel methods of machine learning combining predictions of multiple models to generate a final prediction. This research work have utilized Health Management Information System data which is publicly available on internet by Government of India. But few machine learning models lack explainability which might cause ethical and transparency issues in such critical area like maternal mortality [18].

Traditional machine learning models are mostly transparent and provides clear interpretations on how the model gets to the predictions. Often, exploring the internal working of such models is called interpretable machine learning where the internal working will be explored to create exact patterns of the data. Whereas complex black box models are not easy to understand. The internal working cannot be derived from the models and hence game theoretic approaches are proposed to explain such models. This process is usually referred as explainable machine learning [21]. From the systematic review conducted by [22], it is clear that only few research studies are utilizing explainable machine learning technologies, and Shapley Additive Explanations is widely applied explainable machine learning technique for machine learning models on cross sectional data. The results from explainable machine learning techniques helps us in understanding ways in which a prediction can be interpreted individually. Techniques like Shapley Additive Explanations, Explainable Boosting Machine, etc., can be used to understand the explanations of the maternal mortality predictions and learn facts from the data [23].

The current study is based on the research work that discussed the application of explainable machine learning on studying the factors influencing the maternal mortality ratio of the districts in India using National Family Health Survey data which is used to represent several general factors of districts [23]. Instead of statistical data, the data from Health Management Information System alone is utilized to train machine learning models and further explainable techniques are used to study the data of several districts. This choice of data is because of the nature of the data which is purely medical related and the data is underutilized by researchers [20]. Exploring this data will help us understand new and better insights which help us get a clear understanding on the exact causes for higher maternal mortality ratio in districts.

The choice of health management information system data is completely relevant and necessary for the current study since it is evident that the functional health status of a region can explain the level of occurrence of chronic diseases. Even perceived health status of a chosen region can clearly define the risk of chronic disease associated to the respective region [24]. Few studies have demonstrated the relation between self-assessed health status and socio-demographic factors. Exploring and assessing such type of relations and patterns are essential for social monitoring in a region [25]. Emergency medical services usage also explains the demographic factors of a region like population-level, average medical expenditure of patients at the region [26]. With this study, we will highlight health related factors that impact the maternal mortality ratio of districts of India.

METHODS

Data

Two main indicators that explain the progress of preventing maternal mortality are maternal mortality ratio and number of deliveries attended by skilled birth attendants. Maternal mortality ratio is a measure defined by the World Health Organization which expresses the maternal mortality as number of maternal deaths per 100000 live births.

$$MaternalMortalityRatio = \frac{NumberofMaternalDeaths}{NumberofLiveBirths} * 100000$$

The health management information system data which is publicly available on the Ministry of Health and Family Welfare website are the primary source of data for this paper and this data consists of various health related metrics. Data for the years 2018, 2019 and 2020 are collected from the overall data. The data consists of 198 features out of which two features within the dataset are Number of Maternal Deaths and Number of Live Births. The data doesn't contain any direct target variable which indicates maternal mortality ratio. Hence, with the two available features, the maternal mortality ratio is calculated and these two features are dropped from the dataset.

According to the Sustainable Development Goal target 3.1, all countries maternal mortality ratio should reach to a mark of under 70 by the year 2030. In the year 2024, more than half of the time has been completed since the agreement on sustainable development goals by all countries. Hence, a classification type of problem will be advisable on the data where the target variable indicates whether the district is fulfilling the target of maternal mortality ratio reaching under 70 or not. A new target variable is derived from the existing maternal mortality ratio where the label can be 1 if the maternal mortality ratio ≥ 70 which indicates high maternal mortality ratio, else the label holds 0 which indicates low maternal mortality ratio. This new target is used to train machine learning models assuming this as a classification problem.

Machine Learning

Several machine learning models exist that can be applied on the health management information system data. One black box model that shows almost high accuracy compared to any other machine learning models in general is Random Forest Model [27, 28]. Since Random Forest algorithm is derived machine learning algorithm based on Classification and Regression Trees algorithm where several tree models are trained on random subsets of data. Hence, random forests show high predictive performance compared to other models. For the current study, random forests model is considered with few hyper parameters tuned while training the model. A conventional random forest model follows a voting mechanism to generate the final prediction combining the predictions of all trained tree models. In this study, scikit-learn library is used which implements random forest with a mechanism of averaging the probabilistic predictions to generate final prediction [29]. To observe the difference from ordinary machine learning models in terms of performance, logistic regression, and decision tree models are also trained with same sets of data.

Explainable Machine Learning

Once the machine learning model is trained and performance of the models are observed, explainability of the model should be derived. Several techniques exist for such purpose which are Shapley Additive Explanations, Local Interpretable Model-agnostic Explanations, etc., out of which Shapley Additive Explanations is a popular and widely used choice [30].

To compute Shapley Additive Explanations, a main concept called Shapley values is to be studied. In explainable machine learning, additive feature attribution methods use a common model which can be mathematically formulated as follows.

$$g(z') = \emptyset_0 + \sum_{i=1}^{M} \emptyset_i z'_i$$

where g is the explanation function and f is the estimator function. The above equation represents an explanation model which is a linear function of binary variables z' for M input features, and $\emptyset_i \in \mathbb{R}$ corresponds to the affect on the model's predictions. In case of classic Shapley estimation, the $\emptyset_i$ value can be defined as follows.

$$\emptyset_i = \sum_{S \subseteq F_i} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} [f_{S \cup i}(x_{S \cup i}) - f_S(x_S)]$$

where $S \subseteq F$ is a subset of feature, F is set of all features, $f_{S \cup i}$ is trained on subset of features S including feature i, f_S is trained on subset of features S. These explanation values are generated for each feature for every prediction and then the explanation plots are used to understand the importance of features that contribute to a particular prediction. To implement these approaches, a library on python named shap is used [30].

RESULTS

Exploratory Data Analysis

The maternal mortality ratio of districts are observed for the chosen time period and the patterns of improvement are explored. It is evident that districts are reaching to a mark of low maternal mortality ratio category across time (Figure 2). The range of maternal mortality ratio is gradually reducing but outliers are to be addressed to ensure success of the goal without any disparities across the country.

As on the year 2020 (Figure 3), the number of districts which have achieved the sustainable development goal 3.1 (achieve maternal mortality ratio less than 70) are reaching near to half of the total districts. This is a clear sign of development in terms of maternal health.

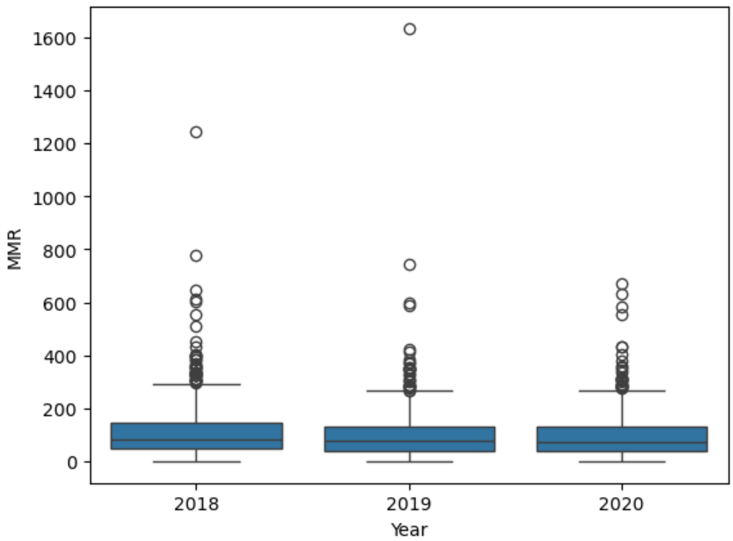

Figure 2 Box Plot for maternal mortality ratio of districts across three years

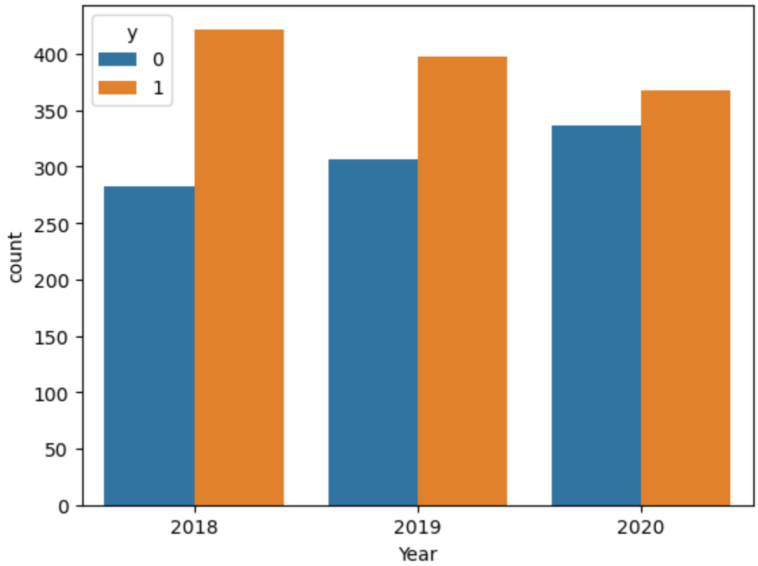

Figure 3 Number of districts that achieved Sustainable Development Goal 3.1 (maternal mortality) across three years

Observing Figure 4, several inferences can be made through observing the plots of different features. Firstly, the total number of pregnant women registered for Antenatal Care is slightly decreasing which should not be the case. Decreasing number of women registered for Antenatal Care in general may influence higher maternal mortality, since antenatal care will help in prevention of mortality. Pneumonia in children seems to be increasing across the three year time period, which may trigger child health related mortality. Whereas Number of fully immunized children is increasing at a good rate, which is a positive sign in curbing maternal mortality. On the other hand, number of c-section deliveries is increasing, which increases risk of maternal mortality. Hence, it is highly unclear on what factors the maternal mortality of a particular district rely on. This encourages application of predictive modeling and explainable machine learning applied on the well performing predictive models to enable policy makers to understand and aid in appropriate dimensions.

Observing the box plot of maternal deaths in Figure 4, there are outliers and the outliers have number of maternal deaths reaching near to 400. This indicates a fact that though the maternal mortality ratio of districts may be lower, it is essential to consider controlling the number of maternal deaths too. Several other features of the data have shown similar patterns and hence, explainable machine learning can address the issue of generating district specific pattern extraction that might help in health policy.

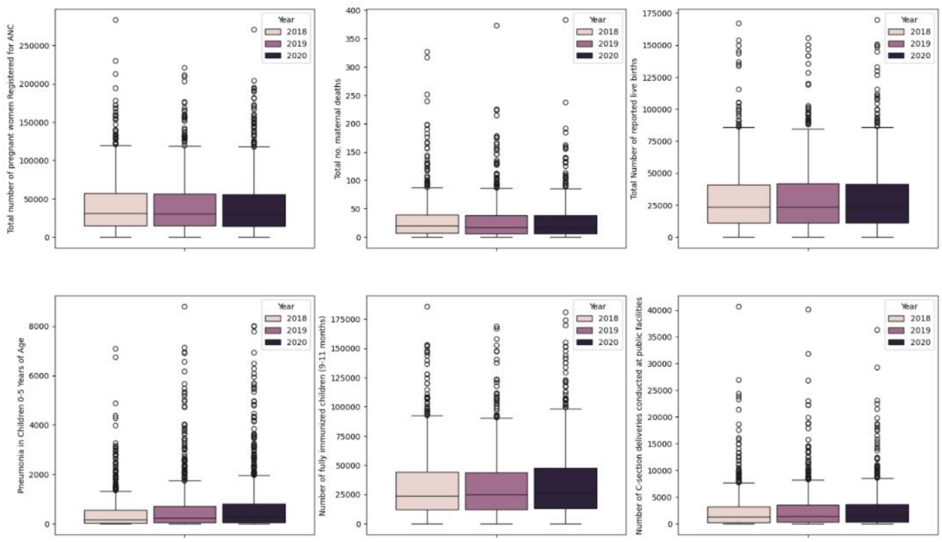

Figure 4 Box plots for few chosen variables of health management information system data

Machine Learning

Three machine learning models are trained on the health management information system data and the performance metrics are noted in order to rule out the low performance models. Out of the three models, which are logistic regression, decision tree, and random forests, random forests turned out to exhibit better performance compared to the other two models.

Model	Accuracy (%)	F1-Score (%)	ROC AUC Score (%)
Logistic Regression	75	78	81
Decision Tree	73	76	75
Random Forest	95	96	99

Table 1 Machine Learning Model Performance

Random Forest model with best parameters has shown the best performance metrics. With maximum depth as 40, minimum samples at leaf node as 2, minimum samples needed for split as 5, and number of estimators as 300, the random forest model works good enough to provide explainability through explainable machine learning algorithms.

Though performance of decision tree is lower than random forests model, a tree structure can be observed to understand basic pattern on how the prediction is made by the model.

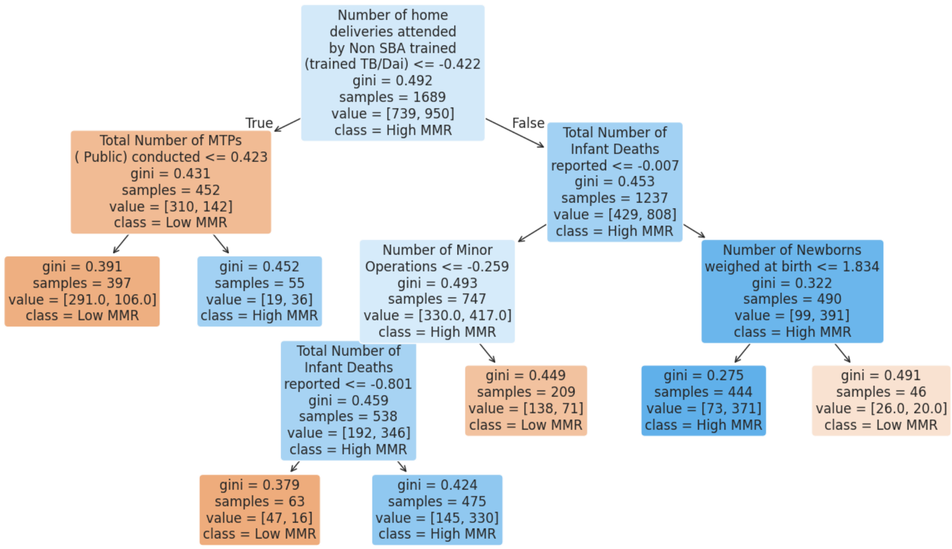

Figure 5 Decision Tree Model on Health Management Information System data

In this structure (Figure 5), the root node is number of home deliveries which separates into two parts where if the value is less than threshold, majorly the district can be classified as low maternal mortality ratio district, else it is classified as high maternal mortality ratio district. Further, assuming the number of home deliveries for the district is less than threshold, check for the number of medically terminated pregnancies. If it is less than the threshold, the district is classified as low maternal mortality ratio district. Similarly the entire tree can be interpreted easily. Unlike decision tree which is an interpretable model, random forest model is a black box model, we have no scope to explore interpretations of the model directly. Hence, Shapley Additive Explanations is applied on the random forests model to derive the explainability.

Global Summary of Explainable Machine Learning

If we observe the global summary plot (Figure 6), Total Number of Infant Deaths reported feature is the top feature that contributes majorly to the predictions. We can observe the higher the value of infant deaths, more probability of random forest model to predict the entry as a higher maternal mortality ratio district. If we observe the same feature, the lower value of infant deaths leads to probability increase in chances of being classified as low maternal mortality ratio district. Similarly, the patterns of other features can be observed. The top 20 features contributing to the predictions globally are available on the current plot. In the health management information system data, the top five features contributing to the predictions in random forests model as per the figure are Total Number of Infant

Deaths reported, Number of home deliveries attended by Non Skilled Birth Attendants, Malaria in Children 0-5 Years of Age, Number of Home deliveries, and Total Number of reported Still Births. We can also observe that these five features holding higher value led to the district falling under high maternal mortality ratio district. Features related to infant mortality are purely exhibiting positive correlation with maternal mortality whereas features related to number of home deliveries impact districts' maternal mortality ratio only for few data entries. That implies every district is not completely depending on number of home deliveries.

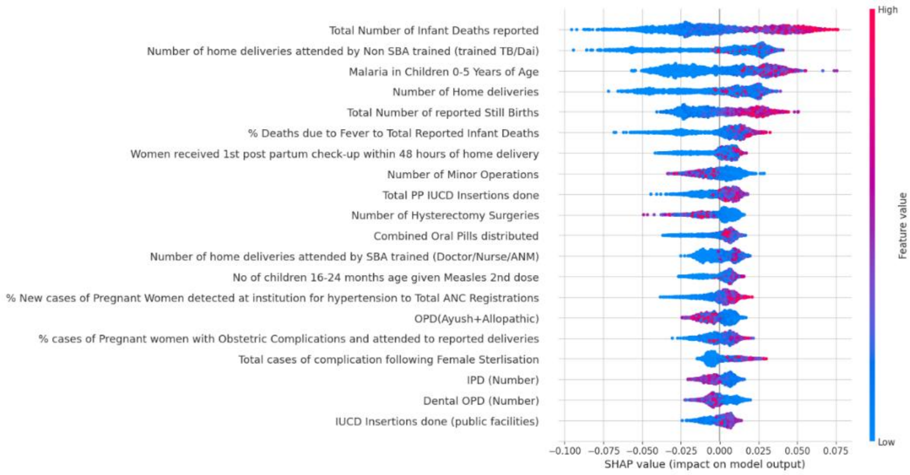

Figure 6 Summary plot from Shapley Additive Explanations on Random Forests model

Since Figure 6 is a summary plot on the entire data, the explanation is oriented towards preventing the mortality all over the country. The objective of current study is to list out factors which help in focussing on regional issues. Figure 7 is a summary plot of the model with Andhra Pradesh state chosen to explore the explainability of lower level region. The top 4 out of 5 important factors that impact the maternal mortality ratio of a district are same as that of the overall data's summary of explainable machine learning. Instead of Total Number of reported Still Births, Women received 1st post partum check-up within 48 hours of home delivery is impacting the maternal mortality ratio of districts in Andhra Pradesh.

Summary of local district level predictions

Two example local explanations of the data are also listed on the report to understand how the results can be interpreted. Two districts, one is Visakhapatnam, Andhra Pradesh which falls under districts with high maternal mortality ratio and other is Warangal Urban, Telangana which falls under districts with low maternal mortality are chosen for local explanations of predictions.

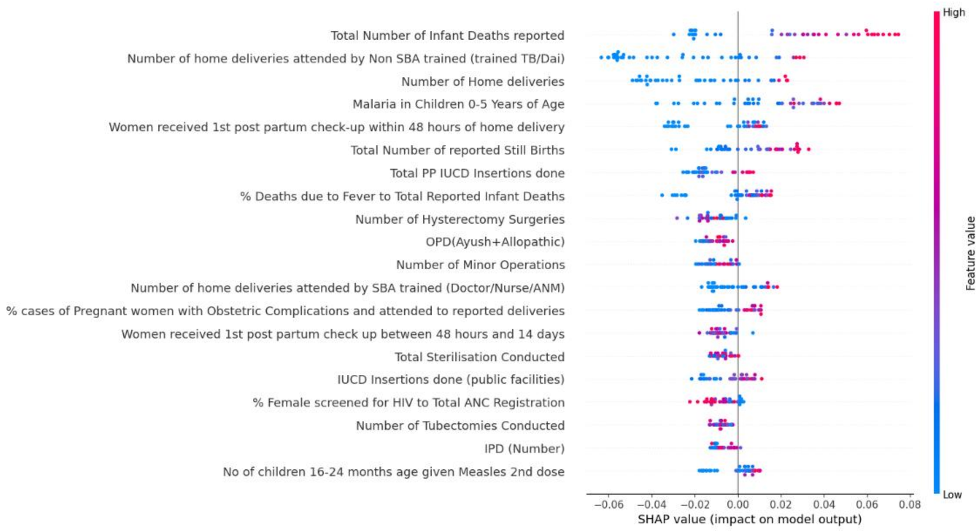

Figure 7 Summary plot from SHAP on Random Forests model (Andhra Pradesh)

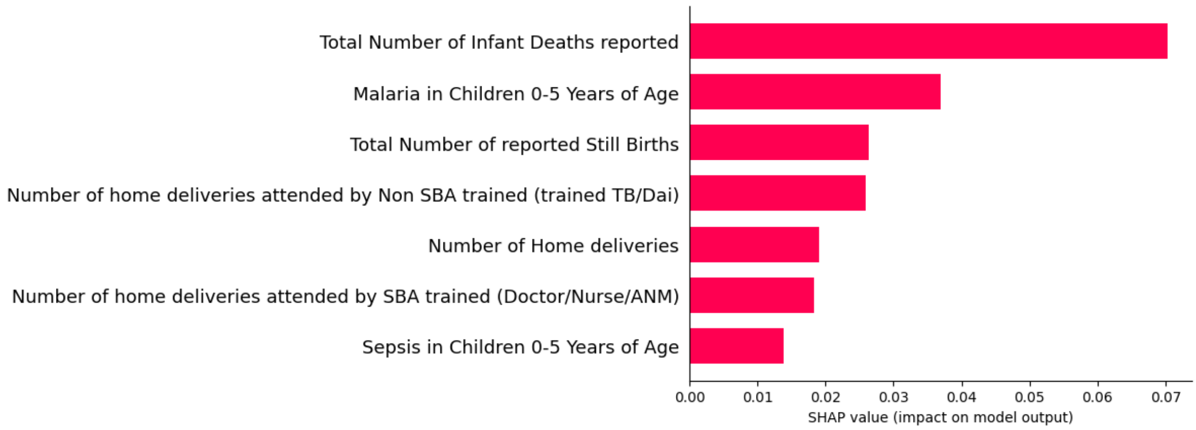

Figure 8 Local explanation of random forest model prediction for Visakhapatnam district

We can examine the local explanation plot where the top 7 features contributing to the prediction of Visakhapatnam district are mentioned in Figure 8. Here, Total number of infant deaths feature is highly leading the prediction towards district with high maternal mortality ratio. Rest of the features, also lead the prediction towards districts with high maternal mortality ratio. Similarly, another district of low maternal mortality ratio is Warangal Urban (See Figure 9). Here, Number of home deliveries attended by Non Skilled Birth Attendant trained, is the top feature pushing the prediction towards low maternal mortality ratio district and even rest of the features also tend to predict the district's target class as low maternal mortality ratio district. Though state level summary tells us the abstract information of all districts of the state, sometimes few districts may show an abnormal pattern due to either cultural disparities or lack of facilities. Such cases can be easily understood using explainable machine learning and will be helpful for public policy decision making.

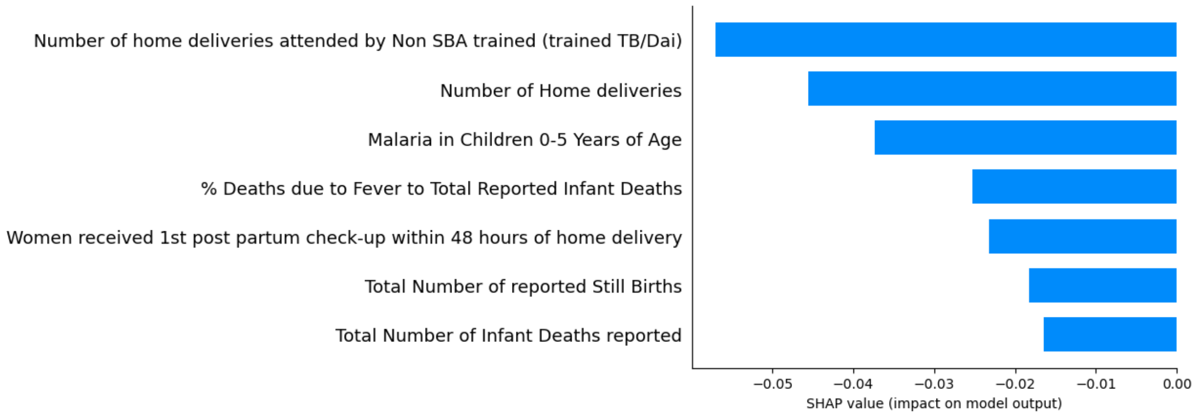

Figure 9 Local explanation of random forest model prediction for Warangal (Urban) district

DISCUSSION

The results of trained model clearly shows a reliance of maternal mortality ratio on more factors related to infants health. Focussing more on curbing infant mortality may even influence in reduction of maternal mortality. Maternal education and women literacy have shown positive influence in reduction of infant mortality, which also impacted the maternal mortality [31]. Some proven methods to estimate the extent of maternal mortality exists at a country level. Studies have proven a relation between Human Development Index and mortality rates. Such frameworks can be made use at district level to study more about the districts' development and controlling of preventable mortality [32]. It is evident that in a chosen area of study, if a maternal death occurs, it is likely to lead to the death of respective infant too. Such cases explain the importance of interchangable focus on both maternal mortality and infant mortality required to end preventable mortality.

Multiple hybrid strategies can be applied in combination with the current study to generate more accurate results and this study is a foundational work that enables application of explainable machine learning on reported health data of a country. The current study is attempted to explore how effectively the insights from a machine learning model trained on health management information system data can be retrieved using explainable machine learning techniques. Applying explainable machine learning on a machine learning project generates more insights than an ordinary predictive model and these insights can aid in decision making process in almost any field.

Most of the complicated patterns can be extracted through machine learning models but unknown patterns will not justify the word ”ethical Aritficial Intelligence” in the modern world. Some critical areas such as Health Care, Logistics, Energy systems, etc., are very sensitive sectors and any inconsistency in information may lead to disastrous situations. Hence, explainable Artificial Intelligence is a required concept in machine learning. Though there are very limited number of resources and implementations related to explainable machine learning, there is a lot of scope for mathematicians and computer scientists to develop advanced techniques.

More complicated modelling like prescriptive analytics and optimization modelling combined with explainable machine learning will enhance the entire insight utilization from the data. Such practices will make sure to boost the efficiency of health systems in India. More data if provided by health management information system may aid in several combinations of input output models being experimented to boost the India’s current position in health care.

Declarations

Ethics approval and consent to participate

Not Applicable

Disclosure of interest

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

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Consent for publication

The authors willingly provide their consent to allow the journal to publish the submitted work unconditionally.

Data availability

The data utilized for this research work is publicly available data obtained from the website of the Ministry of Health and Family Welfare, Government of India.

Materials availability

Not Applicable

Code availability

Not Applicable

Author contribution

All authors have contributed equally in bringing the research work to this level.

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