MATERNAL RISK FACTORS ON NEONATAL MORTALITY

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ABSTRACT:
When a newborn dies within 28 days of birth is termed as Neonatal mortality, is a determining factor of national economic and health status. In this study, the focus is to explore different maternal factors that impact the survival of neonates and identification of risk factors and interventions. With the use of Demographic health survey data, the research would analyze aspects like maternal age, duration of pregnancy, Mother's health during pregnancy, Delivery mode of pregnancy, complications during delivery, tetanus history, exposure to toxic items, and Socio-demographic status. There are various classifiers which are Decision tree, Naive Bayes, Random Forest, Gradient Boosting, k-Nearest Neighbors, and Support Vector Machine (SVM) used to predict the survival of Neonates, assess performance based on precision, determine F1-Score, accuracy, and recall. There is a significant difference observed in results obtained from various classifiers, Random Forest achieved the best precision (68.42%) and F1-score (72.45%) indicated the balanced performance. However, SVM demonstrated highest recall (100%) but showed precision lower to Random Forest. The performance shown by Naive Bayes is poor in precision and recall both. Importance of maternal health and insights for effectual measures to bring down the count of neonatal mortality rate are highlights of this study.

KEYWORDS: Maternal mortality, precision, neonatal mortality, random forest.

RESUMEN:
La mortalidad neonatal, definida como la muerte de un recién nacido dentro de los 28 días después del nacimiento, es un factor determinante del estado económico y de salud de un país. El objetivo de este estudio es investigar los factores maternos que influyen en la supervivencia de los neonatos y identificar los factores de riesgo y las intervenciones asociadas. Mediante el uso de datos de la Encuesta de Salud Demográfica, esta investigación examinará variables como la edad materna, la duración del embarazo, la salud materna durante la gestación, el tipo de parto, las complicaciones durante el parto, la historia de vacunación contra el tétanos, la exposición a sustancias tóxicas y el nivel sociodemográfico. Se utilizan varios algoritmos de clasificación, como el Árbol de decisión, Naive Bayes, Bosque aleatorio, Gradient Boosting, k-Vecinos más cercanos y Máquina de vectores de soporte (SVM), para predecir la supervivencia de los neonatos. El rendimiento de estos modelos se evalúa en función de métricas como la precisión, la puntuación F1, la exactitud y la sensibilidad (recall).Los resultados obtenidos de diferentes clasificadores mostraron diferencias significativas. El Bosque Aleatorio (Random Forest) obtuvo la mayor precisión (68,42%) y puntuación F1 (72,45%), lo que sugiere un desempeño equilibrado y consistente en la predicción. Mientras que la Máquina de Vectores de Soporte (SVM) logró la mayor tasa de recuperación (100%), su precisión fue inferior a la del Bosque Aleatorio (Random Forest). Por otro lado, el clasificador Naive Bayes mostró un rendimiento deficiente en ambas métricas, precisión y recuperación. Los aspectos más destacados de este estudio son la importancia de la salud materna y las recomendaciones para implementar medidas efectivas destinadas a reducir la tasa de mortalidad neonatal.
PALABRAS CLAVE: Mortalidad materna, Precisión, Mortalidad neonatal, Bosque aleatorio
MSC Code: 62P10.

1. INTRODUCTION

The term neonates are used for new born baby. This is a vital indicator of a country's health and economic situation. [11], [7] "When a new birth takes place and the time period starts from the moment of de-attachment of fetus from mother's womb and come to the outside world to start adapting the external environment up to next one month of duration. Neonatal mortality is related to likelihood of survival of neonates during the neonatal period. The World Health Organization (WHO) refers to neonatal death as deaths among live births during the first 28 completed days of life. [13] Neonatal deaths are further classified as early and late neonatal deaths, respectively, with the former grouping deceased between 0 and 7 completed days of birth and the latter grouping deceased between 7 and 28 completed days of birth [23]. In 2020, 2.4-million babies worldwide were deceased away in their first month". It was more or less 6700 babies' deaths every day, amounting to 47% of all child deaths under the age of 5 years, up from 40% in 1990. It has been seen that there was a drastic decline in the deceased neonates between 1990 to 2020 with the figure of 5 million to 2.4 But if we compare it with post- neonatal under- 5 mortalities, then it is relatively more. Nearly one million babies died in the first 24 hours of life in 2019, making the very first week of life the most prevalent period for neonatal deaths (75%).

For an improved neonatal-outcome, it is crucial to identify sick neonates early, provide optimal resuscitation, if necessary, recognize the neonate quickly, and act quickly and competently to treat hypoglycemia, seizures, and respiratory distress. It is also crucial to prevent and treat hypothermia,

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hypoxia, and hypotension, to have adequate monitoring before and during neonatal transport, and to transfer the neonate quickly [9].

A new born baby is very delicate and tender and the fighting ability depends on various maternal factors (external and internal). These maternal factors may impact the fetus in mother's womb.

Detailed study towards investigations in this domain can help us find out the reasons behind the death of baby in his/her neonatal phase. If the causes effect analysis is to be done based on certain factors so by doing what if analysis the parents can be educated about the vulnerability to the life of neonates and precautions and what precautions help them avoid the unwanted circumstances that may occur in future that will help in saving the life of neonates, and suppose in few scenarios in which chances of saving of life is very low then letting this known to parent in advance will help them prepare mentally to cope up with future circumstances. Additionally, the adverse effects of the economic and social side can also be mitigated substantially. Low birth-weight, prematurity, and birth-asphyxia are among the fetal complications that are most strongly linked to maternal factors, including genetic-endowment, sociocultural, demographic, and medical conditions (including., hypertension, malaria, urinary tract infections, malnutrition, and anemia). These factors all act independently [12].

Our contribution in this paper are as follows:

- We have carried out an extensive study on maternal factors
- The selection of significant maternal factors was determined based on R^2 (Coefficient of Determination) value.
- We have examined various approaches: Tree Based (Random Forest, Decision tree), Distance Based (K- Nearest Neighbor), Ensemble (Bagging and Boosting), probability based (Naïve Bayes) and Support vector machine for the prediction purpose of neonatal mortality.

In this study, the aim is to identify the risk factors that may impact the life of new born in order to mitigate the effect of these factors, to save the life of neonates.

The organization of this paper is as follows. Section 2 provides insights into the various maternal factors chosen by researchers and the various classification approaches. Section 3 provides detail about the research methodology used. In Section 4. we have carried out a statistical data analysis. The result and discussion are presented in Section 5. Finally, we have concluded our work in Section 6.

2. REVIEW OF RELATED LITERATURE

Part-A:

During the course of literature review, the different factors that play significant role in survival of neonates have been taken under consideration. Different authors have mentioned some factors these are listed below:

1. Complications during delivery phase of pregnancy: Labor involves intense uterine contractions pushing the baby through the birth canal, but if progress stalls, it's called prolonged labor. This can happen due to factors like a large baby, abnormal position, narrow pelvis, or weak contractions, risking like infections, fetal distress, oxygen deprivation, and shoulder dystocia, which can lead to neonatal mortality if not managed properly [15].
2. Pregnancy duration: Pregnancy duration is classified into the following categories [27].

Pregnancy duration	**Categories**
Before 37-weeks	Pre-Term
Thirty-seven-Weeks-Thirty-eight-Weeks Six Days	Early-Term Thirty-nine-Weeks-Forty-Weeks Six
Days	Full-Term Forty-one-Weeks—Forty-one-Weeks
Six Days	Late-Term Forty-two-Weeks, Post Term

Table 1: Categories of Pregnancy Duration

3. Health metrics - some health metrics act as the determinants for maternal health as well neonates' health.

These are mentioned below

(a) Glucose level (b) Hemoglobin Level (c) Anemia Level [10]

4. Maternal Disease and infection: Diseases and infection carried out by mother is highly likely to be transmitted to baby as it gets everything from the mother through placenta. Some diseases that may have impact are mentioned below

(a) Hypertension (b) Diabetes (c) Heart Disease
(d) Asthma (e) Epilepsia (f) Thyroid
(g) Poly Cystic Ovarian Syndrome (h) Any other [10, 6]

5. Consumptions of any kind of toxic elements may also have impacts on health of neonates. Consumption can be done either directly or indirectly from the surroundings. For example, drinking, smoking, pesticides etc. [4].

6. Adolescence Pregnancy: Mother's age at the time of conceiving also plays an important role towards the growth of a fetus. Age less than 20 years is not considered good to conceive a baby [5]. Mode of Delivery: Delivery of child happens in two modes normal and caesarean. In normal mode, in case of smooth delivery the chances of birth asphyxia is very low where as in case of complicated delivery the chances of birth asphyxia is increased [18].

7. Pregnancy history of mother: There are several factors such as abortion/termination of pregnancy, live births between births, delivery of more than one child etc. that may have impact on baby [8].

8. Socio demographic factor: the environment and surroundings in which mother lives during pregnancy. The education of mother and her partner, their occupation, the consultation visit to the doctor etc. are also playing vital role in the process [3].

9. Tetanus: Ideally two dozes of tetanus vaccine is advised to be taken. In case of miss may cause unwanted infection [21, 25].

The study of existing classifiers in predicting neonatal mortality has led to several key findings. Some relevant studies are summarized below:

The study utilized a range of machine learning algorithms for predicting maternal risks [1]. This approach significantly reduces adverse pregnancy outcomes by enhancing prenatal care through tailored risk assessments. Machine learning algorithms effectively forecast maternal risks, leading to improved prenatal care through personalized assessments.

The paper centers on Logistic Regression, Random Forest, Decision Tree, Support Vector Machine, K-Nearest Neighbors, and Naïve Bayes to predict preterm births using maternal health records in [14]. The predictive power of the models may be limited due to the scarcity of variables. Incorporating important variables could potentially enhance prediction accuracy. The reliance on paper-based maternal health records has led to restricted data availability.

The paper evaluates several machine learning algorithms to assess maternal health risks [23]. However, it does not address Gradient Boosting or Naive Bayes and fails to examine their implications for neonatal mortality. Furthermore, the study highlights a lack of diverse datasets, which restricts the broader applicability of its findings.

The research employed various classifiers to predict maternal health risks [24]. However, it did not explore the use of Naive Bayes, Support Vector Machines (SVM), or Bagging classifiers concerning neonatal mortality. Additionally, the study did not address the real-world challenges of implementation or the need for diverse data sources for model training.

This study aims to benchmark various machine learning models for predicting low birthweight (LBW) outcomes [16]. It highlights the critical role of maternal risk factors, including race, age, and health history, in determining neonatal mortality. Notably, there is a lack of comprehensive studies that evaluate the benchmarking of machine learning models in maternal health, and the real-world performance of these models remains underexplored.

The paper primarily examines the Random Forest algorithm for predicting maternal health risks [19]. Although it references other algorithms, it does not delve into neonatal mortality specifically. Additionally, the study lacks a comparative analysis with other predictive methods and has a limited focus on the challenges posed by rural healthcare infrastructure.

The study centers on utilizing logistic regression, decision trees, random forests, gradient boosting, and XGBoost to classify maternal health risks [20]. It does not delve into SVM, Naive Bayes, KNN, or bagging classifiers in the context of neonatal mortality, nor does it specify the maternal health indicators employed.

The research utilized nine algorithms to predict maternal health risks [17]. The study recommends enhancing prediction accuracy by integrating additional attributes and investigating the potential for real-time implementation in clinical environments.

The study examines the use of a Gradient Boosting Classifier and a Random Forest Classifier for monitoring fetal health [2]. It highlights the application of machine learning techniques in fetal health classification, specifically comparing the effectiveness of Random Forest and TPOT models. However, it does not delve into maternal risk factors associated with neonatal mortality or evaluate other classifiers.

3. RESEARCH METHODOLOGY

This study is based on the input of mother's health condition during pregnancy, history of pregnancy, socio demographic status, tetanus history during pregnancy, mode of delivery, age at the time of birth,

consumption of the toxic elements, complications during delivery phase of pregnancy, duration of the pregnancy etc. and their impact on the survival of new born.
Below steps are performed to get the work done.

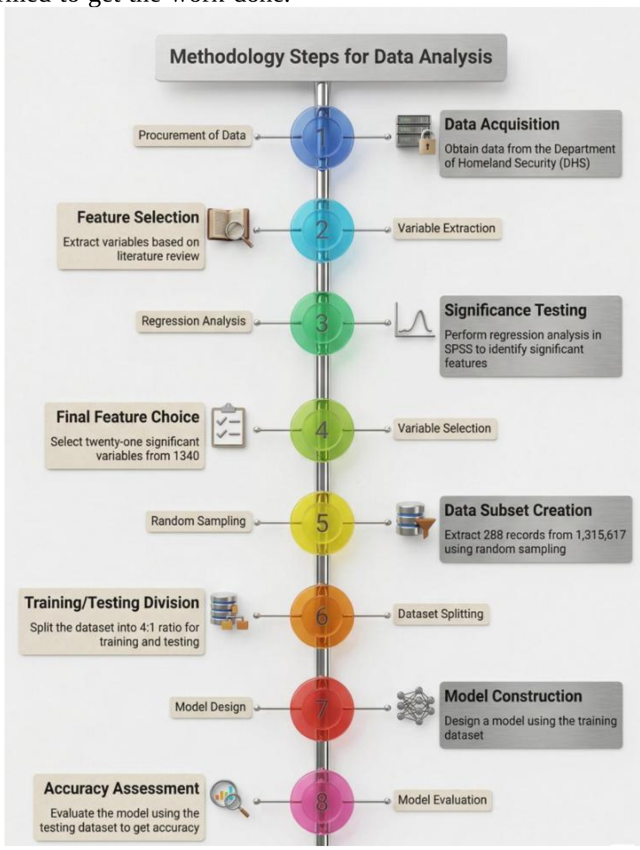

Fig 1: Steps of methodology

Classifiers used: We have used the following classifiers: Gradient boosting, Random Forest, Decision Tree, SVM, Naive Bayes, and KNN.
Performance matrix Used: We have used the following performance matrix for comparison between the various classifiers: Accuracy, and F1-Score.In medical diagnostics, evaluating machine learning models goes beyond accuracy, especially when datasets are imbalanced. The F1 score provides a more nuanced view, balancing precision (correct positive predictions) and recall (identifying actual positives). Unlike accuracy, which can be skewed by predominant negative cases, F1 score ensures models correctly identify disease cases without excessive misdiagnosis, making it crucial for scenarios where missing positives has severe consequences.
Note: 1Missing data set was not random and it couldn't have been imputed.
2Regression analysis done through SPS 3Pre-processing done through MS Excel. 4Designing and evaluation of M/C learning supervised classification model using Python.

Data Collection

The below table gives of the source of the data

Who	Married women of reproductive age (15–49 years) from India, along with their neonatal outcomes, as recorded in the Demographic and Health Survey (DHS) 2015-16
What	Variables based on maternal characteristics and associated neonatal mortality factors, including socioeconomic, demographic, biological, and healthcare-related maternal variables
When	2015–16
Where	India
How	Data accessed from the Demographic and Health Survey (DHS) program with approval.

Table 2: Data Source

Sampling Procedures
We have extracted 23 variables out of 1340 variables using Literature Review and these factors are confirmed using R^2 value.

We have pre-processed the data and have used random sampling to obtain a sample of 288 records out of 1315617 records using a suitable sample size formula as given below.

$$n = \frac{Z^2 p(1-p)}{ME^2}$$

Here n: sample size

Z: Standard Normal Quantile P: Prevalence rate

ME: Margin of Error

Using the basic sample size formula for the large population we have $N = 1315617$, $n = 288$, $p = 0.25$, $Z = 1.96$, $ME = 0.05$

Statistical Data Analysis using Excel

Below table summarizes the regression coefficient of the significant variables:

S.No.	Variable(DHS)	Description	Regression Significant
1	S441	During Pregnancy Complications: Excessive Bleeding	0.036
2	S440	During Pregnancy Complications: Prolonged Labour	0.004
3	S220A	Pregnancy Duration	0.000
4	SB70	Glucose Level	0.000
5	S704	Maternal Disease: Blood Transfusion	0.000
6	M47	Daylight Vision	0.006
7	V212	Age at 1st Birth	0.000
8	V401	C Section	0.000
9	V453	Hemoglobin Level	0.024
10	V457	Anemia Level	0.000
11	V228	Terminated Pregnancy	0.000
12	B15	Live Birth Between Births	0.000
13	V025	Type of place of Residence	0.000
14	V106	Education	0.000
15	V463A	Cigarettes	0.000
16	V463C	Tobacco	0.000
17	V463D	Sniff	0.011
18	V463E	Cigar	0.000
19	V463F	Gutkha/Paan	0.000
20	V463G	Paan with Tobacco	0.000
21	V463Z	Smokes	0.000

Table 3: Factors with their significant coefficient

Note: [1]Age at Death(B6) - Dependent variable

[2]# tetanus during pregnancy= # tetanus injections before birth (M1) - # tetanus injections before pregnancy(M1A)

4. RESULTS AND DISCUSSION

In this work, neonatal threats from maternal perspective have been listed out and analyzed using MS-Excel. In all of the factors considered, we can see from the ANOVA tables that the results are significant. Neural network classification technique is used to build the predictive model. This model consists of two hidden layers with sigmoid and relu activation function. The accuracy of the model is 64.27. Due to covid-19 pandemic, this work was carried out on secondary data from Demographic Health Survey. It could have been improved if the analysis would have been done on primary data with the listed factors. Different classifiers were applied on the data and computed performance metrics in terms of precision, recall, accuracy, and F1 Score that are shown in Table 4.

Classifier	Accuracy	F1 score
Gradient Boosting	0.577576	0.695117
Random Forest	0.615747	0.724492
Decision Tree	0.551089	0.638791
SVM	**0.650218**	**0.788014**
Naive Bayes	0.448113	0.336973
KNN	0.581205	0.699203
Bagging	0.54717	0.636364

Table 4. Classifier Results

Among all the classifiers viz Gradient Boosting, random Forest, Decision tree, SVM, Naïve Bayes, KNN, Bagging, we can see that Support Vector Machine (SVM) achieved the highest F1 score of 0.78 and the highest accuracy of 65%, which indicates effective detection of neonatal mortality while simultaneously providing reliable predictions of neonatal mortality. This is followed by Random Forest, KNN and so on.

While probability based classifier Naïve Bayes has got the minimum F1 score of 0.33 and minimum accuracy of 44%. Hence from the table we can see that SVM has performed best as compared to all other classifiers.

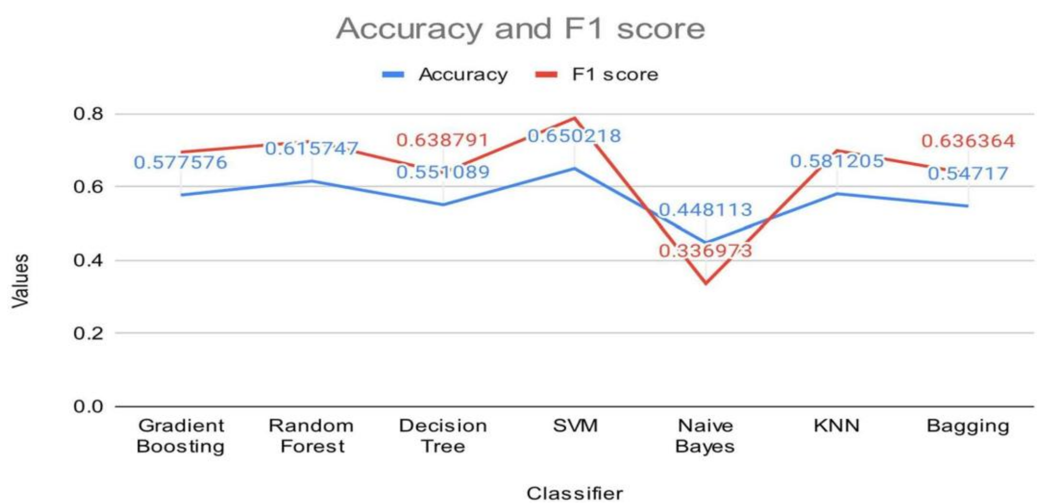

Fig 2. Graphical representation of the results

In this medical diagnostic task, Support Vector Machine (SVM) emerges as the top performer, boosting the highest F1 Score (0.79) and accuracy (0.650), indicating a strong balance between precision and recall. Gradient Boosting and k-nearest neighbors (KNN) follow closely, with F1 scores around 0.67. Random Forest, Decision Tree, and Bagging show moderate performance (F1 scores:0.62-0.64), with model interpretability being a potential deciding factor. Naïve Bayes underperforms significantly (accuracy:0.448, F1 score: 0.337) and is not recommended due to high misdiagnosis risk.

5. CONCLUSIONS AND FUTURE WORK

The aim of this study is to find out the risk conditions in advance so that the parents could be made aware of it before the birth. That will help them prepare to cope up with the future challenges in terms of economic, social, and emotional fronts. The survival of neonates depends upon the mother's health condition during pregnancy, history of pregnancy, socio demographic status, tetanus history during pregnancy, mode of delivery, age at the time of birth, consumption of the toxic elements, complications during delivery phase of pregnancy, duration of the pregnancy etc. This study can be performed on secondary data. In a medical setting, the cost of a wrong prediction can be very high. Therefore, it is crucial to choose a model that not only has high accuracy but also a high F1 score. The Support Vector Machine (SVM) is the most suitable classifier as it demonstrates the best ability to balance the trade-off between correctly identifying patients with the disease and avoiding false alarms. While other models like Gradient Boosting and KNN also perform well, SVM stands out as the most robust and reliable model.

In future it can be done on primary data. Number of variables can also be increased to perform analysis in wider context. This study has covered the neonatal mortality, further it can be extended to the perinatal mortality and birth defects as well.

The significant variables are excessive bleeding during pregnancy and hemoglobin level and yes, they make sense from medical point of view. The other factors pertaining to toxicity does not have that much significant impact. Through this study, we aim to mitigate the mortality of the neonates by controlling the significant maternal factors. This in turn will bring out improvement in the survival of neonates and better maternal health outcomes. It will also contribute to reduce infant mortality rate. As a result, it will improve the overall family well-being and quality of life.

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