



Comparison Of Artificial Neural Network and Decision Tree Methods for Predicting the Maternal Outcome in A Tertiary Care Hospital in Odisha, India

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ABSTRACT

Background: This study used an artificial neural network (ANN) and a decision tree to predict maternal outcomes and their major determinants. An artificial neural network (ANN) and a decision tree were used in this study to determine maternal outcomes and their significant determinants.

Methods: Data was gathered from 955 pregnant women at a tertiary care hospital in Bhubaneswar, Odisha. A popular machine learning algorithm, artificial neural networks (ANN), was used to predict maternal outcomes and their determinants.

Results: In the bivariate analysis, we found gestational age is significantly associated with maternal outcome ($p < 0.001$). The accuracy of the ANN model and decision tree was 0.882 and 0.823, respectively. Based on the variable importance of ANN, the significant determinants of maternal outcome were birth weight, systolic blood pressure, haemoglobin, gestational age, age of mother, diastolic blood pressure etc.

Conclusion: This model can be utilized in future for Proper precautions and medical check-ups required during the maternal period to avoid a negative maternal outcome.

Keywords: Machine learning, maternal outcome, Classifier, Decision tree, ANN

INTRODUCTION

An expectant mother passes away every minute. It is unacceptable that so many mothers die young¹. Adolescent girls are at a higher risk of maternal mortality². The gap between the wealthy and the poor is made more evident by the increase in maternal fatalities. During their pregnancies, women in rural communities are ignored. Due to clinical staff members' reluctance to work in remote areas, the majority of childbirths take place at home with untrained attendants, no experienced midwives, and a shortage of clinical professionals. Maternal mortality is made worse by women's lack of education. Delay in receiving medical attention owing to inadequate

transportation and bad roads are one factor in maternal mortality³.

Nearly 75% of maternal deaths are caused by serious complications. Risky abortion, anaemia, eclampsia, and infections are a few of the consequences. The inadequate medical management infrastructure is one of the serious effects of maternal death. Hospitals provide insufficient attention and inefficient treatment for women⁴. Women are dying because of inadequate facilities in healthcare facilities not only in rural areas but also in many developing countries. The hospitals don't even have enough operating rooms for emergency caesareans, leaving the women with no choice except to wait in the hallway until their turn to receive a usable room. As a result, pregnant

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women are more likely to experience adverse maternal and neonatal outcomes.

By 2030, the maternal mortality ratio (MMR) should be significantly lower than 70 per 100,000 live births, according to the Sustainable Development Goals (SDGs)⁵. The majority of maternal deaths are preventable; all women must receive top-notch care during and after birth. Health care workers with the necessary training and experience must attend every birth. The hospitals ought to have enough operational operating rooms for C-the section. Enhancing prenatal care and identifying high-risk pregnancies early can help prevent difficulties during delivery and lower maternal mortality⁶. This study aims to find association between maternal outcomes with other independent/predictor variables. And to create a suitable predictive model which will be useful for the clinicians.

Related work

A similar literature review was conducted in order to properly analyse the data. We restricted our search to research on pregnancy outcomes that used predictive modelling. Rakesh et al.⁷ used a comparison of logistic regression and decision tree methods to predict environmental factors in preterm birth. Rakesh et al based his work in this paper on a comparative study of two predictive modelling algorithms. Using predictive modelling, the author identified significant factors for preterm birth. The significant preterm birth factors in his study were malondialdehyde, α -hexachlorocyclohexane. Kidanemariam et al. presented a suitable predictive model for stillbirth prediction in Ethiopia. The authors used logistic regression analysis to identify risk factors for stillbirth.⁸ Using an artificial neural network, Kwang-Sig Lee et al. investigated Spontaneous Preterm Labor and Birth and Its Major Determinants⁹. Leon J. Schmidt used machine learning methods to improve the prediction of preeclampsia-related adverse outcomes¹⁰. Tarini et al. developed a suitable predictive model for predicting adverse maternal effects in preeclampsia at term¹¹.

MATERIALS AND METHODS

Study Design and Setting: Retrospective data were collected from obstetrics and gynaecology department from June 2021 to December 2021. We included 327 (34.2%) cases (adverse maternal outcomes) and 628 (65.8%) good maternal outcome from 955 pregnant women. We collected data from the hospital for six months. The maternal outcome was the dependent variable in this study. Age, gravida, parity, placental position, blood group, mode of delivery, systolic blood pressure, diastolic blood pressure, AFI, birth weight, and HB were the independent variables. Usually, adverse maternal outcome is defined by low blood pressure, lower haemoglobin level, bad placental position and lower birth weight after delivery, whereas good maternal outcome defined as vag-

inal delivery, normal blood pressure with normal birth weight.

Objective

This study's goal was to identify the critical variables influencing maternal outcomes and forecast those results using an appropriate statistical machine learning technique.

Statistical Analysis: SPSS V25 was used to generate decision tree and ANN. IBM SPSS is good prediction model software for model development and validation²⁷ we used a chi-square test for the dependent and independent variables in a bivariate analysis to determine their relationship. In order to check for a significant difference in the continuous variables, we also ran a student t-test. Due to the decision tree's ability to generate a binary tree, which is useful in classification problems, we employed it in both the training and the entire datasets in this instance. We split our data into a training set (70 per cent) and a testing set (the remaining 30 per cent), which we used to construct and validate our data set (30 per cent). Following that, we separately ran a decision tree and an artificial neural network on our data set. Training set and testing set are used for internal validation of a predictive model. Training set usually often subset of the data which is used to build a predictive model and testing set or validation set is used to find accuracy of the model.

Artificial Neural Network and Decision Tree

Our objective is prediction and pattern identification in many of the scenarios. Artificial neural networks (ANNs) are developing technology for pattern detection and prediction in current circumstances. In disciplines like Linear Regression, Logistic Regression, Decision Trees, etc., numerous machine learning algorithms are employed for prediction and classification applications. A new machine learning method for pattern detection and prediction is the artificial neural network.^{12 13} Recent viral prediction techniques utilized in healthcare, public health, and medical research include artificial intelligence, machine learning, and deep learning. Data analysis methodologies, model evaluation, model accuracy, model validation, scalability, and convergence can all be accomplished with ANN^{13 14}.

The advantage of ANNs is their quick processing of large amounts of real execution, which has increased the demand for research in this area¹⁴. For example, we can process natural language using the ANN model. Due to their exceptional self-learning capabilities, adaptability, responsibility tolerance, nonlinearity, and advancement in input-to-output mapping, ANNs are now usually used in numerical paradigms for global function approximation¹⁵.

Predicting and pattern identification in various industries is simple with the new tools of artificial intelligence and machine learning approaches. These prediction techniques are used by many industries, including finance, banking, education, and

healthcare, to improve data accuracy and clinical implementation.¹⁶ The artificial neural network (ANN) model is regarded as a developing machine learning approach globally^{17 18}.

Decision tree: In machine learning, the decision tree is one of the best nonlinear data modelling techniques. It is a supervised machine learning technique for categorizing data. The role of the decision tree is to divide the data into binary splits and continue until further breaks occur. The structure of the decision tree is similar to that of a tree, with decision nodes and branches.

RESULT

We conducted a bivariate analysis on our data to determine the relationship between independent variables and maternal outcomes, and we found no association between gravida and the maternal outcome ($p=0.546$). Similarly, with a p -value of 0.558, the analysis shows no association between parity and maternal outcome. Maternal outcome was strongly related to gestational age ($p=0.001$). We discovered 33 (3.5%) cases with gestational age 28+0 - 32+6WK,

172 (18%) patients with gestational age 33+0 - 36+6WK, 728(76.2%) cases with gestational age 37+0 - 40+6WK, and 22(2.3%) cases with gestational age 41 + 0 weeks. Furthermore, overall gestational age was found to be strongly related to maternal outcomes. The placental position, on the other hand, was not associated with the maternal effect, with a p -value of 0.203. Likewise, the blood group ($p=0.062$) and mode of delivery (0.994) were unrelated to maternal outcomes.

When the significant difference in mean was examined, it was shown that there was no significant difference in the age group between favourable and unfavourable maternal outcomes ($p=0.701$). The average age of the women was 27.09 ± 4.34 . Systolic blood pressure significantly varied on average ($p < 0.001$). The group with a good maternal result had lower systolic blood pressure than the group with a poor maternal outcome, we discovered. Similarly, the mean difference in diastolic blood pressure was significantly different ($p < 0.001$). Here, we saw that the group that had a positive pregnancy outcome had lower diastolic blood pressure than the group that had a negative pregnancy outcome.

Table 1: Association of categorical variables with the maternal outcome

Variables	N=955	Good maternal outcome	Adverse maternal outcome	P-Value
Gravida				
Primigravida	545(57.1)	354	191	0.546
Multigravida	410(42.9)	274	1361	
Parity				
Nulliparous	620(64.9)	408	212	0.558
Primipara	293(30.7)	192	101	
Multipara	42(4.4)	28	14	
Gest Age				
28+0 - 32+6WK	33(3.5)	3	30	<0.001
33+0 - 36+6WK	172(18)	51	121	
37+0 - 40+6WK	728(76.2)	558	170	
≥41 + 0 WK	22(2.3)	16	6	
Placental Position				
Anterior	445(46.6)	296	149	0.203
Posterior	297(31.1)	203	94	
Lateral	90(9.4)	51	39	
Fundal	123(12.9)	78	45	
Blood Group				
RH -VE	12(1.3)	7	5	0.062
O+VE	365(38.2)	240	125	
A+VE	220(23.0)	129	91	
B+VE	300(31.4)	213	87	
AB +VE	58(6.1)	39	19	
Mode Of Delivery				
VD	435(45.5)	286	149	0.994
LSCS	520(54.5)	342	178	

Table 2: Association of continuous variables with the maternal outcome

Continuous variables	Overall (Mean±SD)	Good maternal outcome (Mean±SD)	Adverse maternal outcome (Mean±SD)	P-Value
Age	27.09±4.34	27.13±4.14	27.02±4.711	0.701
SBP	115±10.93	114.10±7.528	118.94±15.029	<0.001
DBP	75±8.92	74.04±6.365	76.89±10.472	<0.001
HB	11.52±3.51	11.608±4.217	11.355±1.384	0.292
AFI	10.95±4.35	11.442±3.705	9.957±5.277	<0.001
Birth Weight	2753.91±621	2949.34±422	2380.41±756	<0.001

Between the two groups, the mean haemoglobin level did not differ significantly ($p=0.292$). We discovered a p -value-significant difference in mean AFI between the two groups $p<0.001$. The mean birth weight between the two groups was highly influential, $p<0.001$. The analysis revealed a meagre birth weight in adverse maternal outcomes (2380.41 ± 756) compared to good maternal outcomes (2949.34 ± 422).

Gestational age, systolic blood pressure, diastolic blood pressure, AFI, and birth weight were determined to be significant predictors for a mother outcome in the investigation mentioned above utilizing statistical approaches, as we found that increase in risk factors from normal range could result adverse effect in mother and child also. In order to perform a better and more in-depth research, we applied two popular machine learning techniques to forecast the model's maternal outcomes and crucial parameters.

A decision tree and ANN were used in the creation and validation of our model. For this, we separated our data into the training set and the testing set. For the ANN model, the overall model performance was remarkably strong. Our research revealed that the model can accurately predict 88 percent of the situations, which is quite good. The critical normalized scores for each variable were discovered in our study (fig 1). Variable importance is determined by calculating the relative influence of each variable, which is done by the software. The model demonstrates that the first crucial factor for the maternal outcome is birth weight (0.22). Similar to this, the most important necessary determinants for maternal outcome are systolic blood pressure (0.17), AFI (0.12), haemoglobin (0.11), and gestational age (0.1). (Fig 1)

Decision tree based on association with most significant variables, it uses CHAID (Chi square automatic interaction detection) principle to build the tree. The decision tree deals with interaction between the most significant variables with the dependent variable. Node 0 is the head of the decision tree which is showing in (fig 2). The best predictor of maternal outcome is birth weight ($p<0.001$). Birth weight is clustered into 4 segmentation node 1, node 2, node 3, node 4. Node 1 is suggesting that if birth weight of the baby will be <1900 gram, 97.9% cases will be adverse maternal outcome whereas 2.1% cases will be good maternal outcome. Node 2 indicating that if birth weight of the baby ranges between 1900-2320 gram 57.9% of cases will be adverse maternal outcome and 41.1% cases will be good maternal outcome. Node 3 represents that if birth weight of the baby ranges between 2320-2685, 70.7% will be good maternal outcome and 29.3% will be in adverse category. if Birth weight >2685 the decision tree predicts that 78.6% of cases will be good category whereas 21.4% cases will be in adverse category. Similarly gestational age was also a significant predictor according to decision tree with $p<0.001$.

Hence using Chi square automatic interaction detection, the decision tree was built in fig 2.

Table 4 is given for comparison between two model performances. The sensitivity of ANN and Decision tree was 0.90 and 0.86 respectively. similarly other parameters of predictive model such as specificity, F1 Score, AUROC (area under receiver operating curve) was compared between two models. it was observed that ANN predicts slightly more accurately (0.88) as compared to decision tree (0.82). Hence in this comparison we may say that ANN performed better than decision tree to predict maternal outcome.

Table 3: Normalized importance of variables created by Artificial Neural Network

Independent Variable	Importance	Normalized Importance
Gravida	0.014	6.2%
Parity	0.044	19.2%
Gestational age	0.095	41.0%
Blood group	0.055	23.6%
Placental position	0.035	15.2%
Mode of delivery	0.015	6.5%
Age	0.043	18.7%
SBP	0.148	63.8%
DBP	0.103	44.5%
Hb	0.087	37.7%
Amniotic fluid index	0.129	55.7%
Birth weight	0.231	100.0%

Table 4: Assessment of classification models on Performance metrics

Performance metrics	Model	
	ANN	Decision tree
Accuracy	0.88	0.82
Sensitivity	0.90	0.86
Specificity	0.85	0.81
F1-score	0.88	0.83
AUROC	0.97	0.87

DISCUSSION

The results of numerous research in the past indicated that a healthy pregnancy for the mother depends greatly on the baby's birth weight.^{19 29} The birth weight of the child is crucial for a positive mother result, as we have discovered in our study using an artificial neural network and decision tree. Moreover, we found from our research that a pregnant woman's success depends on the birth weight of her child. Furthermore, discovered that any variation from the average in a baby's birth weight raises a risk factor for pregnancy. Baby birth weight variations may be caused by Stress, excessive exercise, maternal diet, smoking, alcohol intake, and other factors. Another important aspect in our study that our models accurately predict is systolic blood pressure. When we compared positive maternal outcomes with negative maternal impacts in the primary analysis, it was also noted that there was a significant difference in systolic blood pressure.

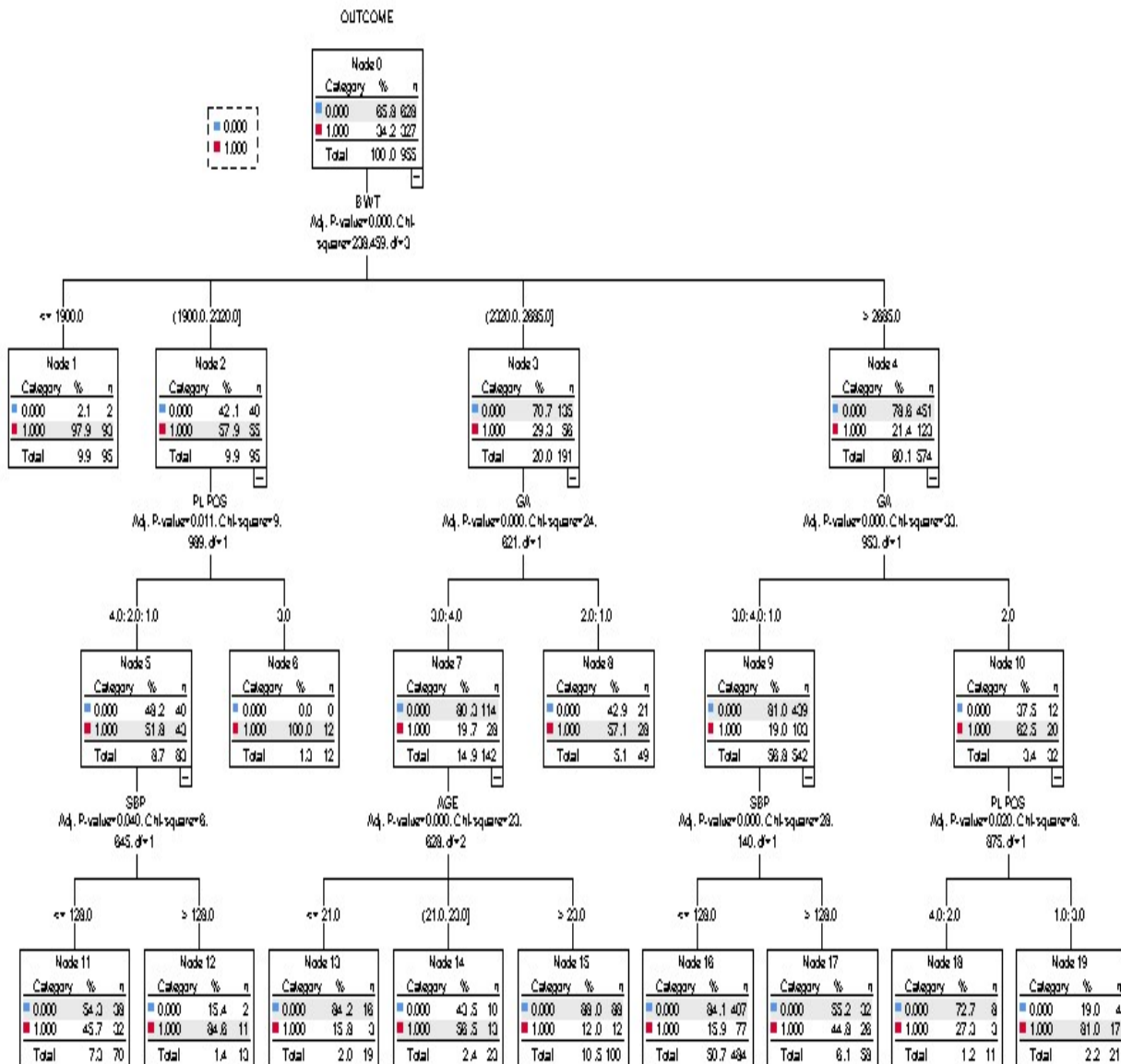


Figure 2: Decision Tree Classification trained model of maternal outcomes

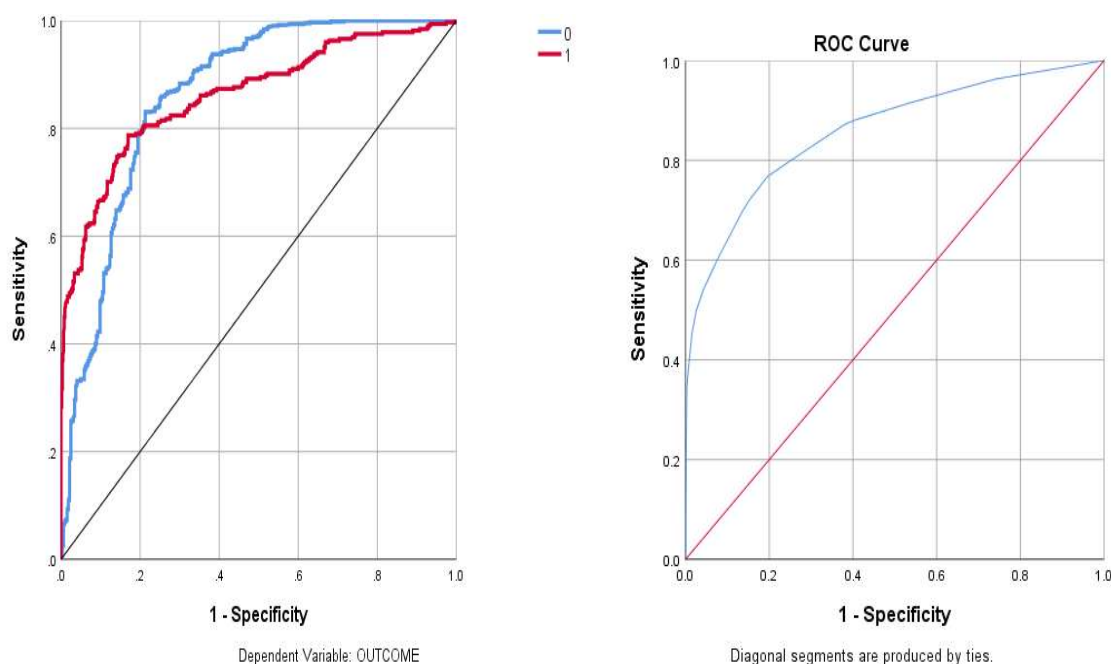


Figure 3: Comparison between Roc curve for ANN (left) and Decision Tree Model (right)

Systolic blood pressure is an additional significant factor in our study that our models successfully predict. Our analysis revealed that systolic hypertension was found to be strongly related with higher risk later in life. We should test the predictors of systolic pressure status in various populations that we have identified. The variables we have identified as predictors could be applied in clinics to pinpoint high-risk women who need to get early intervention. Counseling mothers with low birth weight, high systolic blood pressure, low hemoglobin, high diastolic blood pressure, high gestational age, and other risk factors can be one of these therapies. Systolic blood pressure, hemoglobin, gestational age, mother's age, and diastolic blood pressure status should all be closely monitored in addition to the baby's birth weight. Additionally, these intervention measures might be helpful in enhancing maternal health status and preventing negative functional outcomes for women.

To ascertain the relationship between AFI and maternal outcomes, several researches have been carried out.²⁰ The majority of studies focus on prenatal effects and AFI that is on the edge. A strong correlation between amniotic fluid content and maternal outcome was found in the majority of investigations²¹. It is essential to the development of the mother and fetus throughout pregnancy.²² In this investigation, we discovered that the AFI between the two groups varied significantly. AFI is ranked as the third most crucial component for positive maternal outcomes, according to the artificial neural network.

Many studies show that the presence of anaemia during pregnancy increases the likelihood of a negative maternal outcome.^{23,24,25,28} We discovered that hemoglobin is one of the most important factors in the maternal effect using a decision tree and an artificial neural network. A low haemoglobin level raises the possibility of adverse maternal outcomes.

Our study found a significant relationship between maternal outcome and gestational age, which many other studies have found.²⁶⁻²⁹

CONCLUSION

Understanding machine learning algorithms' application to healthcare data is the result of this work. Here, we have used artificial neural networks and decision tree approaches to assess the data and draw recommendations that may be useful for the doctor as well as for the safety of the patients. Our findings also showed that an artificial neural network outperforms a decision tree model in terms of classification accuracy for maternal outcomes. In order to better validate our data, future studies will incorporate a deep learning system. With the help of ANN, we discovered that birth weight of baby, systolic blood pressure, hemoglobin, gestational age, age of mother and diastolic blood pressure can all be viewed as potential risk factors for pregnancy related deaths.

These risk factors are directly related with the negative maternal outcome. This study could be set as benchmark for decreasing death rate during pregnancy and after birth of baby.

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