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Deep Learning Based Risk Level Prediction Model For MaternalMortality

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ABSTRACT
Maternal health refers to the wellbeing of women throughout pregnancy, childbirth, and the postpartum period. Every time a woman becomes pregnant, she runs the danger of a sudden, unforeseen complication that could result in both her death or injury and the death or harm of her unborn child. It is estimated that 170 million pregnancies occur annually around the world. Pregnancy complications are health issues that develop while a woman is pregnant; some women experience these issues while others experience them before to conception. This work attempts to investigate the potential application of Logistic Regression, Random Forest, Adaboost, KNN, Catboost, XGboost, 1-D CNN and ANN for predicting and analysing difficulties in women, driven by the rise in the use of machine learning techniques in the research dimensions of medical diagnosis. The Maternal Health dataset from the Kaggle repository, which has 7 attributes and 808 records, is used to assess the proposed strategies. Using the Spyder IDE and a few packages and modules, all of the project's algorithms were implemented in Python. Results strongly indicate that 1D-CNN based prediction models function better on all datasets with greater accuracy of 99.53% after using various machine learning approaches, deep learning techniques, and handling missing values.

Keywords: Health Risks, High blood pressure (BP), Deep Learning, Artificial Neural Network (ANN), 1D - Convolutional neural network (CNN), Adaboost, Catboost, XGboost, K-Nearest Neighbor(KNN), Logistic Regression(LR),Random Forest.

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I. Introduction

Pregnant women often die from complications due to inadequate information about maternal health care during and after pregnancy, especially in rural areas and in low-middle-class households in developing countries. women who die during pregnancy, childbirth, or in the first 42 days following the termination of their pregnancy, from any cause related to or exacerbated by the pregnancy. It is a significant public health concern worldwide, with approximately 830 women dying every day due to preventable causes related to pregnancy and childbirth, according to the World Health Organization (WHO). At least 40 percent of all pregnant women will experience some type of complication during pregnancy. For about 15 percent, the complication will be potentially life-threatening and will require post- obstetric care. About 60 million women suffer from complications from pregnancy, also known as maternal morbidity. For more than 15 million women these morbidities are long-term and often debilitating.

The majority of maternal deaths occur in low-income and middle-income countries, where access to quality healthcare is limited. The most common direct causes of maternal problems are excessive blood loss, high blood pressure, infections, unsafe abortion, diabetes, epilepsy, thyroid disease, heart and blood disorders, poorly controlled asthma, and unsafe abortion. Other factors are smoking cigarettes, drinking alcohol, and using illegal drugs can put a pregnancy at risk. Enhancing maternal health is essential to preserving the lives of the more than 500,000 women who pass away each year due to difficulties during pregnancy and childbirth. Factors that raise the risk of maternal mortality include poverty, illiteracy, and inadequate nutrition

Reducing maternal mortality is a global health priority, and the WHO has set a target of reducing the global maternal mortality ratio to less than 70 per 100,000 live births by 2030. The underlying causes of maternal mortality must be addressed by comprehensive and integrated initiatives, which should improve access to high-quality maternal healthcare services, support women's education and empowerment, and address social and economic inequities.

1.1 Causes of Maternal Mortality

The causes of maternal mortality can be extensively classified into:
Direct causes Indirect causes

Direct causes: Direct causes of maternal mortality are those that are straightway related to gestation or childbirth.The most common direct causes of motherly mortality include

- Severe bleeding(postpartum hemorrhage)
- Infections(similar as sepsis and tetanus)
- High blood pressure during gestation (pre-eclampsia and breakdown)
- Complications from delivery(such as obstructed labor or ruptured uterus)
- Unsafe abortion

Indirect causes: Indirect causes of maternal mortality are those that aren't directly related to the pregnancy orparturition but are complicated by the physiological effects of pregnancy. Common indirect causes include

- Pre-existing medical conditions (such as diabetes, heart disease, or HIV/ AIDS)
- Malnutrition and anemia
- Inability to obtain good maternal healthcare services
- Poor sanitation and hygiene

1.2 Signs and symptoms of Maternal Mortality

Maternal mortality can occur suddenly and without warning, but in some cases, there may be warning signs or symptoms that healthcare providers can look for. Some of the symptoms that could indicate a potential risk of maternalmortality include:

- Severe bleeding: Excessive bleeding is one of the most common symptoms of maternal mortality. Women who experience heavy bleeding after childbirth or have bleeding that does not stop after delivery should seek medical attention immediately.
- Difficulty breathing: Shortness of breath, rapid breathing, or chest pain could indicate a pulmonary embolism or other serious respiratory condition that could lead to maternal death.
- Seizures: Seizures or convulsions during pregnancy or after delivery could indicate a serious medical condition such as eclampsia or pre-eclampsia, which can lead to maternal mortality if not treated promptly.
- High blood pressure: Women who experience high blood pressure during pregnancy (pre-eclampsia) may be at risk of maternal mortality. High blood pressure, hand and foot edema, and protein in the urine are all signs of pre-eclampsia.
- Severe headache: Severe headaches during pregnancy or after delivery could be a symptom of pre-eclampsia or other serious conditions, which could lead to maternal mortality if not treated promptly.

1.3 Effects of Maternal Mortality

- Emotional trauma: The death of a mother can have a profound emotional impact on her family, especially her children, and can lead to long-term emotional and psychological issues.
- Economic impact: The death of a mother can leave her family without a source of income, especially if she was the primary caregiver and breadwinner. This can lead to increased poverty and decreased access to basic needs such as food, shelter, and education.
- Reduced productivity: When women die during pregnancy or childbirth, they are unable to contribute to the workforce and their communities, which can have a negative impact on economic growth and development.
- Reduced fertility: The death of a mother can also reduce the chances of her children surviving and thriving, which can lead to decreased fertility rates in the affected community.
- Health impact: The death of a mother can lead to increased health risks for her children, such as malnutrition and poor health outcomes, due to decreased access to care and resources.
- Societal impact: High rates of maternal mortality can have a negative impact on the social and economic development of a country, as it can lead to decreased access to education and healthcare, lower life expectancy, and increased poverty rates.

II. Literature Survey

Raza A, Siddiqui HUR, Munir K et al in [1] stated that using photos, health records, and time-series data, deep learning-based models have been applied to a wide range of medical applications like disease prediction. These models assist academics and medical practitioners make speedy and precise diagnoses by revealing hidden patterns in medical data. This study uses deep neural models to predict health risks associated with pregnancy in light of recent applications, suitability, and efficiency of deep learning models. It also proposed a novel deep neural network architecture that takes into account decision trees, Bidirectional long short-term memory (BiLSTM), and temporal convolutional network (TCN) to create DT-BiLTCN for feature extraction. the usage of n to train machine learning models later. Support vector machines (SVM), extra tree classifiers (ETC), logistic regressions (LR), and decision tree classifiers (DTC) are employed in this context to forecast the danger to a woman's maternal health during pregnancy. Moreover, a BiLTCN ensemble model made up of BiLSTM and TCN is employed. The maternal health exploratory data analysis (MHEDA) is carried out to research the medical issues that act as the most reliable indicators to foretell various threats to the mother's health during pregnancy. In essence, two factors data resampling for data balance and fine-tuning of the proposed model's hyperparameters additionally improve the performance of the DT- BiLTCN. The health dataset in this study is balanced using the synthetic minority oversampling technique (SMOTE), and hyperparameters are modified to choose the set of hyperparameters that perform the best. Several current models are compared with the suggested approach to assess their effectiveness. The efficiency they gained by applying these models is 98%.

Marzia Ahmed and Mohammod Abul Kashem et al in [2] stated a Model for monitoring a pregnant woman's health and that of the fetus. To analyze medical data and determine risk levels, IoT environments have collected and transferred data both locally and in the cloud. According to the recommended methodology, data was combined from several sources. A medical data set has been prepared using combined data using weka and python machine learning techniques for additional analysis and prediction. Low risk, mid risk, and high risk are the three categories of risks that have been taken into consideration. The overall number of entries is 1014, of which 406 were considered to be at low risk, 336 to be at mid-risk, and 272 to be at high risk. Weka and Python have both been used to create groups of machine learning algorithms; as a result, the decision tree provides a maximum accuracy of 97%. To obtain the optimal parameters, the classifier was tweaked using GridSearchCV, a hyperparameter tuning technique. Also, a few data mining and statistical procedures such as the Chi-square test, Info gain, Gain ratio, etc. have been used to identify key factors.

Lakshmi.B.N, Dr.Indumathi.T.S and Dr.Nandini Ravi et al in [3] observed that Every woman's life is sensitive during pregnancy, and the health of pregnant women changes for a variety of reasons, including changes in hormones, blood pressure, temperature, weight, blood glucose levels, infections, and other factors. Hence, using two classification algorithms—decision tree classification algorithm and Naive Bayes Classification Algorithm—they created a project to anticipate the current health complications inflicting on a pregnant woman. These methods were chosen because they are frequently used to perform the classification and prediction tasks in data mining. The investigation is separated into four phases: data gathering, preprocessing, analysis, and model evaluation. Data collection is the initial phase of the study. The study is divided into four phases, the first being the data collection phase, second the data preprocessing phase, the third data analysis phase and lastly the model evaluation phase. A total of seventeen parameters are considered for the study like, age, present state, date of conceiving, present month of pregnancy, present trimester, pregnancy parity, history of pre-eclampsia, history of gestational diabetes, family history of preeclampsia, family history of gestational diabetes, Blood Pressure (BP), Presence of gestational diabetes, height, previous weight, present weight and weight gain. So, the accuracy of each parameter is crucial for pregnant women's health. The total accuracy obtained is 59%.

Galih Malela Damaraji, Adhistya Erna Permanasari and Indriana Hidayah et al in [4] identified that in the world of medicine, there isn't a flawless expert method for identifying hazards during pregnancy. The current state of the Expert-System and its application in the medical sphere, notably risk identification during pregnancy and support for decision-making when there is a high risk of pregnancy, will thus be covered in this article. They also discussed several methods for developing expert systems that are related to pregnancy risk and how the expert system will aid in predicting pregnancy risk in expectant mothers. This research addresses and categorizes knowledge-based techniques into five groups: a rule-based, fuzzy expert system, artificial neural networks, machine learning, and other techniques along with its application to identify medical issues experienced by pregnant women. These publications' analyses revealed the hazards of hypertension, early birth, abnormal pregnancies, and ectopic pregnancies. They discovered some drawbacks and benefits of these rule-based systems, including the fact that a bigger training set is frequently unnecessary and that because the expert's thinking is clearly described, it is possible to understand how he approaches issues. The main benefit of fuzzy expert systems is that they will conform to important norms in human language rather than computer code. The average accuracy value in the ANN study yields excellent results. It receives positive feedback from many different angles, but the ANN requires additional data for testing and training to produce more accurate results. There have been a lot of studies done on the diagnosis of high-risk pregnancies. They concluded that Artificial Neural Networks and Rule-based systems account for the majority of application development using expert system

John Mark Bautista, Quiel Andrew I. Quiwa and Rosula S.J. Reyes et al in [5] observed the High rates of maternal and fetal mortality have been seen in the Philippines, primarily as a result of the absence of qualified medical personnel, high-quality healthcare, and easily accessible health facilities in rural and isolated regions. This study suggests using the Telemedicine framework to assist physicians and other healthcare workers. The input of patient information, a mobile application for data input and visualization, a cloud-based server for the database, and a machine learning system that examined patient profile data comprised the setting for the Telemedicine technique utilized in prenatal care. The machine learning system was developed using Decision Tree, Random Forest Decision Tree, K-Nearest Neighbor, and Support Vector Machine as its four implemented algorithms. Accuracy, precision, recall, and the F1 score—the weighted average of precision and recall—were used to measure each algorithm's performance. The Random Forest Decision Tree, which has a 90% accuracy rate, is the most efficient algorithm to apply based on the performance metrics.

Rohan D'Souza, Ruxandra Pinto and Andrea Hill et al in [6] identified that In the ICU or on a regular ward, various prediction models have been used on pregnant and postpartum women. They set out to study and analyze risk prediction models for maternal mortality in hospitalized and critically sick pregnant and postpartum women in a systematic manner. 38 studies that created and/or validated 12 models for predicting mortality among hospitalized pregnant and postpartum women were found in this systematic review. The Maternal Severity Index for hospitalized general obstetric populations and the Collaborative Integrated Pregnancy High-dependency Estimate of Risk (CIPHER) for critically ill pregnant and postpartum populations both have good discrimination and calibration, were developed from studies with low risk of bias, and have been internally and/or externally validated for these populations. They concluded that the Collaborative Integrated Pregnancy High Dependency Estimate of Risk (CIPHER) model and the Maternal Severity Index, two mortality risk prediction models developed from obstetric patient populations, have good discrimination and calibration and were developed/validated from studies with a low risk of bias. While there is some risk of over- or underestimating mortality in prediction models previously created from general and non-obstetric patient populations, such as the APACHE, MPM, SAPS, and SOFA scores, they typically have good discrimination and can be used when pregnancy-specific models are not available.

III. Dataset

Dataset for this research purpose has been collected from the Kaggle Repository which is publicly available from Kaggle repository. The detailed summary of the dataset is given below:

Table 1: Details of Dataset

SI.NO	Dataset Name	Sources	Attribute Type	Number of Attributes	Number of Instances
1.	Maternal Health Risk Dataset	Kaggle Repository	Categorical, Continuous, String type andBinary	7	808

The dataset has 7 attributes that are used for prediction. These attributes are listed below:

Table 2: List of Attributes in the dataset

SI.NO	Attributes Description	Data type
1.	Age	Number
2.	Systolic Blood Pressure	Number
3.	Diastolic Blood Pressure	Number
4.	Blood Sugar	Number
5.	Heart Rate	Number
6.	Body Temperature	Number
7.	Risk Level	String

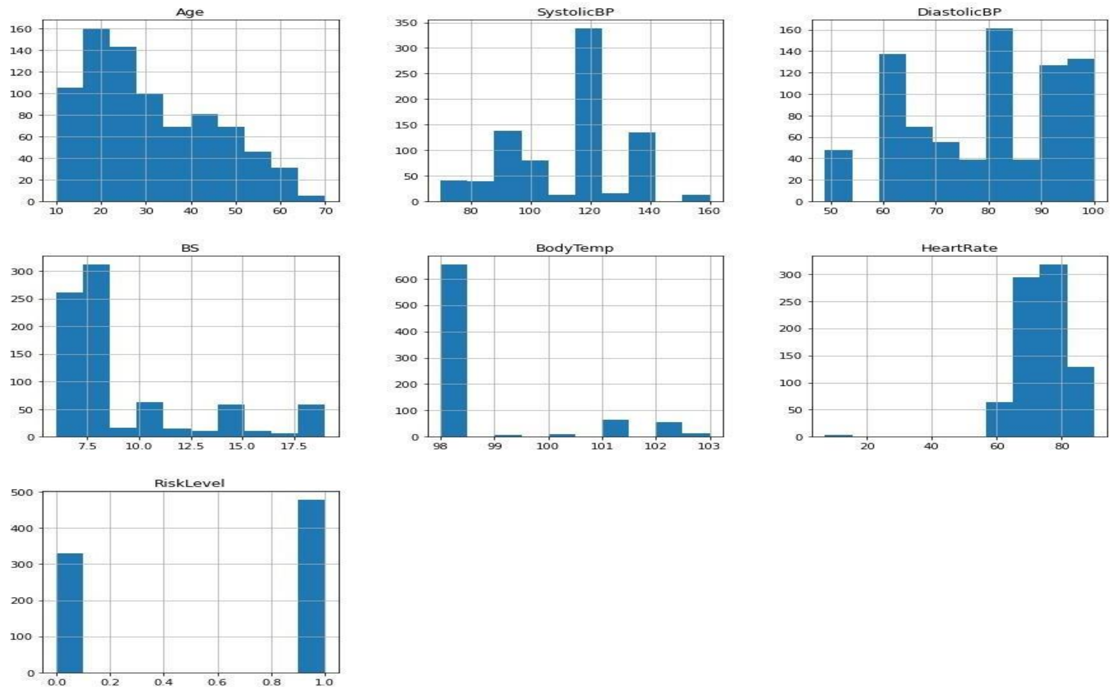


Figure. 1. Histplot for attributes in Maternal Health Risk Dataset

IV. Proposed Methodology

Figure 1 shows the steps in the proposed workflow which involves the pre-processing of data, training, and testing with specified models, evaluation of results and prediction of Maternal Mortality. This work is implemented in Python 3.

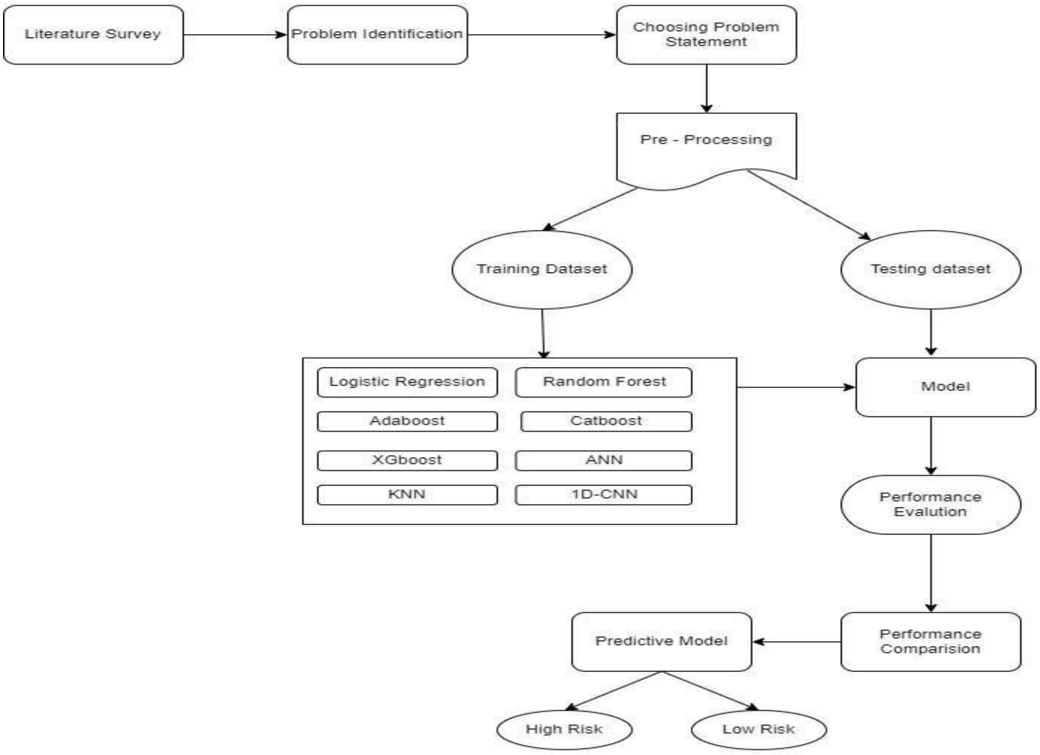


Figure. 1. Steps in the proposed Maternal Health detection solution

a. Data Pre-Processing

Data pre-processing is a technique that transforms the raw data into a meaningful and understandable format. Real- world data is commonly incomplete and inconsistent because it contains lots of errors and null values. Good, pre-processed data always yields a good result. Various Data pre-processing methods are used to handle incomplete and inconsistent data like as handling missing values, outlier detection, data discretization, data reduction (dimension and numerosity reduction), etc. The problems of missing values in these datasets have been handled by the imputation method.

b. Training and Testing Model

The whole dataset has been split into two parts i.e. one part is training dataset and the other one is testing dataset with a ratio of 80:20 respectively. Figure 2 shows the final training, testing and validation sets on which classification has been performed.

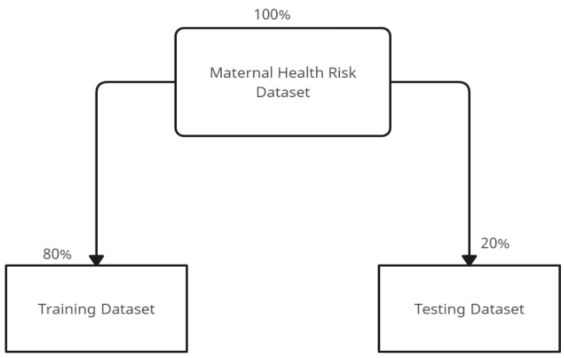


Figure. 2. Final Training and Testing Dataset

4.2.1 Logistic Regression

Logistic regression is a binary classification algorithm that models the probability of a binary outcome (e.g., yes/no, true/false) based on one or more predictor variables. The algorithm works by estimating the coefficients of a logistic function that maps the input features to the output probability. The logistic function is a sigmoid curve that squashes the output values between 0 and 1, representing the probability of the positive class. Logistic regression is simple, efficient, and can handle both categorical and continuous data. It is widely used in various fields, such as healthcare, finance, and marketing, for predicting binary outcomes and understanding the relationships between predictors and outcomes. The logistic function used in logistic regression is defined as:

p(x) = 1 / (1 + e^(-z))

where p(x) is the probability of the binary outcome, x is the input feature vector, and z is the linear combination ofthe input features and their corresponding weights.

4.2.2 Random Forest

Random forest is an ensemble learning algorithm that combines multiple decision trees to improve the accuracy and robustness of the predictions. The algorithm works by building a large number of decision trees on bootstrapped subsets of the training data and randomly selecting a subset of features at each node. The output of the random forest is the average or majority vote of the individual tree outputs. Random forest is robust, scalable, and can handle both categorical and continuous data. It is widely used in various fields, such as bioinformatics, finance, and ecology, for classification, regression, and feature selection tasks.

4.2.3 AdaBoost

An ensemble learning system called AdaBoost (Adaptive Boosting) combines several weak learners into one powerful learner. The algorithm trains a weak learner iteratively on a weighted subset of the training data, with the weights being changed according to the accuracy of the prior weak learner. A weighted combination of the weak learner outputs is what the AdaBoost algorithm produces as its result. Both categorical and continuous data can be handled using AdaBoost, which is effective and versatile. It is frequently used for classification and regression problems in many different domains, including bioinformatics, computer vision, and speech recognition.

4.2.4 CatBoost

CAT (Categorical and Continuous Attributes) is a gradient boosting algorithm that is designed to handle both categorical and continuous data. The algorithm works by partitioning the data based on the categorical features and using gradient boosting on the continuous features. This allows the algorithm to capture the interactions between the categorical and continuous features, leading to improved accuracy. CAT is efficient, scalable, and can handle missing data and high-cardinality categorical features. It is widely used in various fields, such as e-commerce, healthcare, and marketing, for classification and regression tasks.

4.2.5 XGBoost

XGBoost (Extreme Gradient Boosting) is a gradient boosting algorithm that is designed for speed and performance. The algorithm works by iteratively adding weak learners to a model, where each learner tries to correct the errors of the previous learner. XGBoost uses a regularized objective function to prevent overfitting and can handle both categorical and continuous data. The algorithm also supports parallel processing, tree pruning, and early stopping to improve performance and reduce computation time. XGBoost is widely used in various fields, such as finance, healthcare, and computer vision, for classification, regression, and ranking tasks.

4.2.6 K-Nearest Neighbor (KNN)

The supervised machine learning method KNN (K-Nearest Neighbors) is utilised for both classification and regression applications. The algorithm works by finding the k closest instances in the training data to a new instance, and then predicting the output based on the majority or average of the k nearest neighbour outputs. KNN is simple, non- parametric, and can handle both categorical and continuous data. The algorithm is also sensitive to the choice of distance metric and the number of neighbours (k), which can affect its performance. KNN is widely used in various fields, such as bioinformatics, image recognition, and recommendation systems.

4.2.7 1D Convolutional Neural Network (CNN)

1D CNN (Convolutional Neural Network) is a deep learning algorithm that is designed to process 1-dimensional data, such as time series or signals. The algorithm works by convolving the input data with a set of learnable filters, which capture local patterns and features in the data. The output of the convolutional layer is then passed through a nonlinear activation function and pooled to reduce the dimensionality. The resulting feature map is fed into one or more fully connected layers for classification or regression. 1D CNN is efficient, robust to noise and variability, and can automatically learn useful representations of the data. It is widely used in various fields, such as speech recognition, finance, and biomedical signal processing. A simple diagram of CNN is given below:

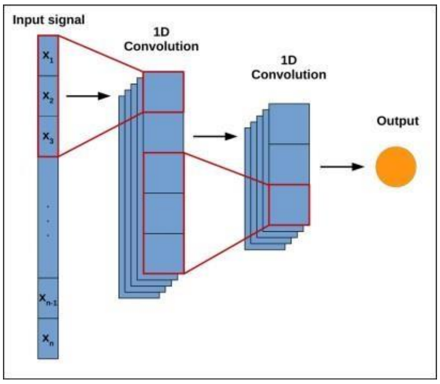


Figure. 3. 1D CNN

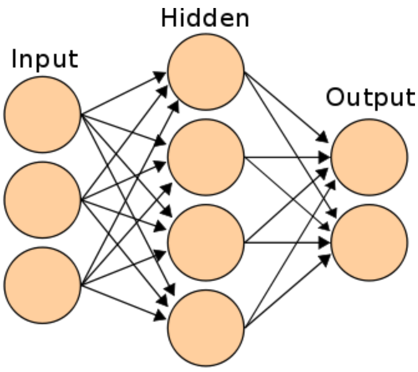


Figure. 4. Artificial Neural Network

4.2.8 Artificial Neural Network

ANN is a neural network that has a connection with multiple neurons. Every neuron cell has a set of input values and corresponding weights. The feeds forward neural network is the most used artificial neural network.. In this network,the flow of information moves in the only forward direction. The input layer, the hidden layer, and the output layer are the three primary layers of this kind of network. The input layer is the first layer. The network contains no cyclesor loops.

V. Result and Discussion

The result is measured in terms of Accuracy, F1- Score, Precision Score and Recall Score by using the confusion matrix and classification report. The result depends on how accurate the model is trained.

a. Performance Evaluation metrics

Measuring performance is key to check how well a classification model work to achieve a target. Performance evaluation metrics are used to evaluate the effectiveness and performance of the classification model on the test dataset. It is important to choose the correct metrics to evaluate the model performance such as confusion matrix, accuracy, specificity, sensitivity, etc. Following formulas are used to find the performance metrics:

Table 3: Elements of a Confusion Matrix

Predictive MHD Values		
Actual MHD Values	True Positive (TP)	False Positive(FP)
False Negative(FN)	True Negative(TN)	

$$\textbf{Precision Score} = \frac{\textbf{TP}}{\textbf{(TP+FP)}}$$

$$\textbf{Recall Score} = \frac{\textbf{TP}}{\textbf{(TP+FN)}}$$

$$\textbf{F1- Score} = \frac{\textbf{TP}}{\textbf{TP+1/2(FP+FN)}}$$

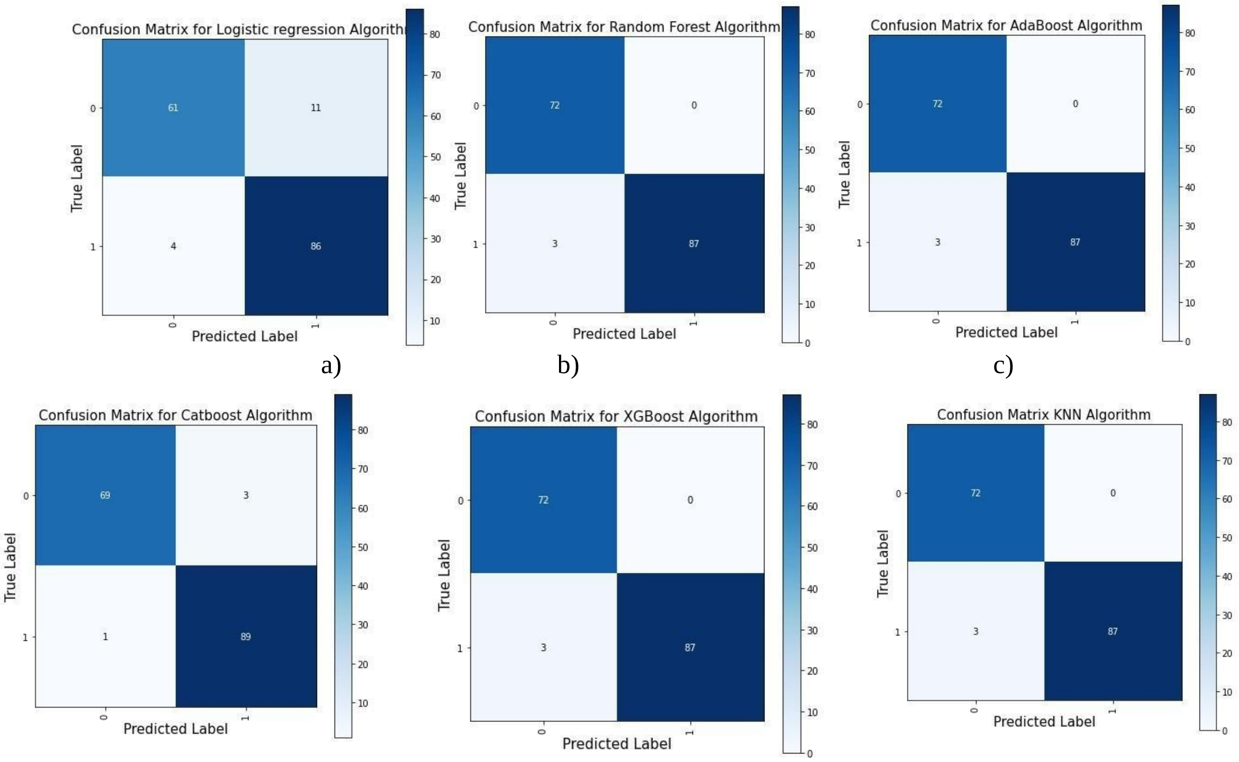
$$\textbf{Accuracy} = \frac{\textbf{TP+TN}}{\textbf{(TP+FP+TN+FN)}}$$

Experimental results of various machine learning and deep learning algorithms approach with all features selection have been shown for Maternal Health Risk data. In this, all 7 features are selected to find the precision, F1-Score, Recall and accuracy of the predicted model. For the implementation of ANN, Adam Optimizer ,100 epoch and binary cross-entropy loss function has been used. In CNN, Relu activation Function, Adam Optimizer, binary cross-entropy loss function, 16 & 32 filters and 0.5 dropouts with 100 epoch has been used. The Overall performance measures of all machine learning and deep learning classifiers with the mentioned dataset have been shown below in details:

Table 4: Overall Results for Maternal Health Risk Data using Machine Learning Algorithms

Classifier	**Precision Score**	**Recall Score**	**F1- Score**	**Training Accuracy**	**Testing Accuracy**
Logistic Regression	86.67	87.46	87.27	87.46	90.74
Random Forest	98.60	98.60	98.60	98.60	98.14
Ada Boost	98.60	98.60	98.60	98.60	98.14
Cat Boost	97.05	97.05	97.05	97.05	97.53
XG Boost	98.60	98.60	98.60	98.60	98.14
KNN	98.60	98.60	98.60	97.36	96.29

Evaluation of various machine learning models on Maternal Health Risk dataset observed an accuracy in the range of (90.74% to 98.14 %) on the original dataset. Logistic Regression has produced the least accuracy of 90.74%. Random Forest, AdaBoost and XGBoost have produced 98.14 % prediction accuracy on the original dataset. The confusion matrixes of all Machine Learning algorithms also describe the results of the prediction model.



a) b) c)

d) e) f)

Figure 5: Confusion Matrices for Different Machine Learning Algorithms

Comparison of various machine learning algorithms can be done by plotting a line plot. Below mentioned line plot will show case the comparison among algorithms, based on that it can be easy for us to conclude a best fit algorithm for our proposed work.

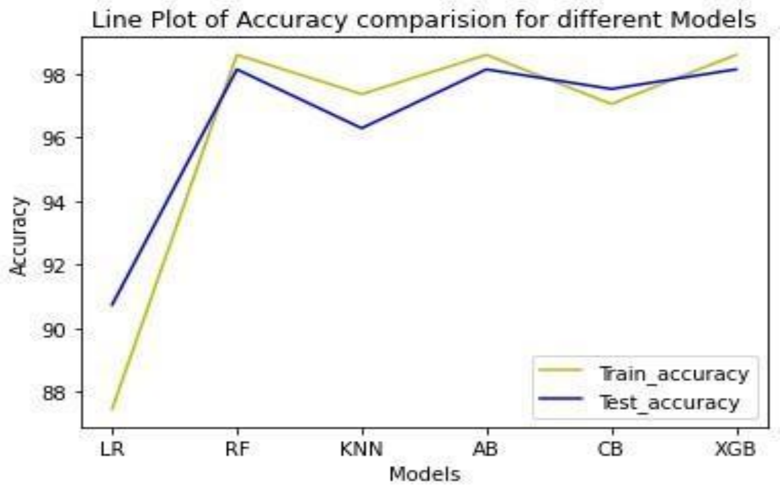
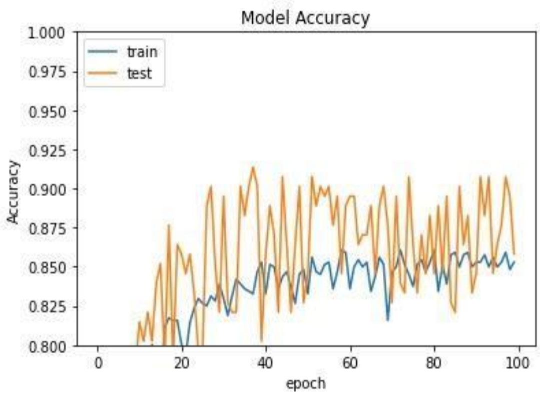


Figure 6: Bar Plot for Various Machine Learning algorithms

When our dataset is applied on various deep learning algorithms like Artificial Neural Network (ANN) and One Dimensional Convolutional Neural Network (1D-CNN) those algorithms are performed well and produced high accuracies compared to machine learning algorithms.



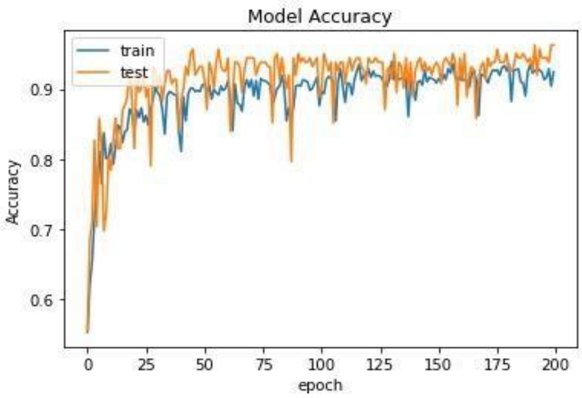


Figure 7: Accuracy plot for ANN. Figure 8: Accuracy plot for 1D CNN

VI. Conclusion

In this work, detection of Maternal Health Risk was attempted using various machine learning and deep learning techniques. Various performance evaluation metrics were used to analyse the performance of the models implemented for Maternal Health Risk detection on Maternal Health Risk Dataset. When we compare results between machine learning and deep learning algorithms, In those deep learning algorithms are performing well. Mainly 1D CNN in some cases perform very well and produce up to 98.34% accuracy. Likely ANN also perform very well when it compare with other machine learning algorithms and gives up to 90% accuracy

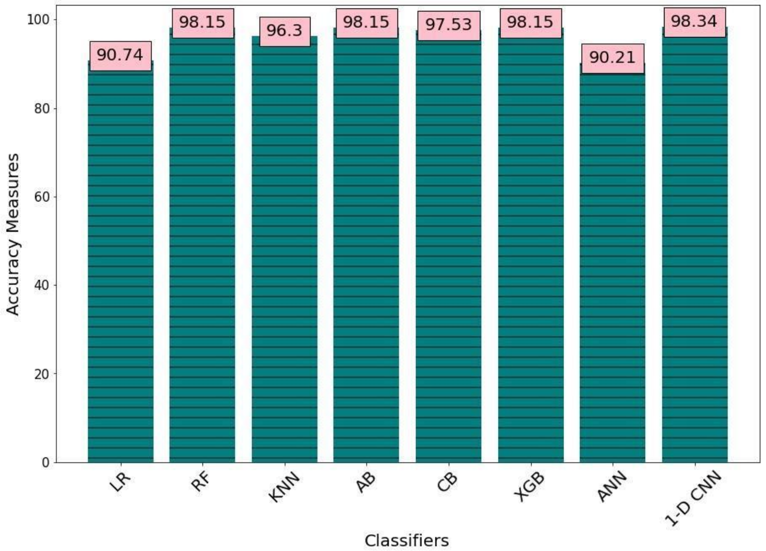


Figure 9: Testing accuracy comparison of Various Deep – Learning Algorithms with Machine Learning Algorithms

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