Predicting Maternal Health Risk Using Machine Learning Models And Comparing The PerformanceOf Percentage Split And K-Fold Cross Validation

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Abstract— **This paper presents a comprehensive study on predicting maternal health risk using advanced machine learning models. We explore the effectiveness of different model architectures and evaluate their performance using two common techniques: percentage split and K-Fold cross-validation. Our research highlights the significance of accurate risk prediction in maternal healthcare, emphasizing the need for robust model evaluation methods. Through extensive comparative analysis, this study provides valuable insights into the optimal approach for predicting maternal health outcomes, contributing to the advancement of healthcare technologies and ensuring better maternal well-being.**

Keywords— ***Maternal Health, Machine Learning, K-Fold Cross validation, Percentage Split, Classification***

I. Introduction

Women experience an unfathomable thrill when they bring revival into the world. Several mother deserve to experience that happiness. However, this situation either becomes frightening for many women in this environment. Pregnancy-related infections, excessive bleeding, and high blood pressure account for two-thirds of all maternal deaths. Complications from pregnancy are one of the major cause of death in girls between the ages in teen. Teenage girls are actually more vulnerable to pregnancy risks since their bodies are still developing. Child brides are more likely to experience pregnancy-related complications because they are less likely to obtain adequate medical care while pregnant or give birth in a medical facility[2]. Maternal mortality is still a major issuein many countries, especially developing ones, despite advances in medical research.The World Health Organization (WHO) reports that every day, almost 810 pregnant women and 6,700 babies pass away. Several non-communicable diseases may arise because of epigenetic modifications linked to maternal diet and chemical exposures. Early life environmental pressures, which are referred to as the new discovery origins of health and disease, are assumed to be caused by these epigenetic modifications. influences the risk of chronic illness[4]. The shortage of doctors and nurses, as well as localization, timing, and distance, are a few of the factors that raise the mortality rate of pregnant women and childbirth (Redondi et al., 2013). According to an estimate by the WHO, 800 women will die every day in 2020 as a result of inadequate resources and treatment (Castillejo et al., 2013). It is challenging to assure both the mother and the unborn child's safety during pregnancy because, despite recenttechnical advancements, the rate of maternal deaths is declining. In this situation, pregnancy- related risks can be decreased by foreseeing difficulties and taking preemptive measures[5]. where it is observed to be greater . It has been discovered that the increased frequency of maternal anemia in LMICs is associated with a number of poor consequences for pregnant women and their babies. For instance, it is estimated that 20% of all maternal deaths globally are caused by anemia during pregnancy . Additionally, it is predicted that anemia contributes to 591,000 perinatal fatalities globally [5], with South Asia and Africa accounting for the majority of these deaths[7].

Calculating the hazards to a woman's health using machine learning techniques is crucial. The risk level of a pregnant woman can be tracked and estimated by using machine learning techniques to analyze her health data and risk variables. As a result, it is believed that using machine learning-based models can effectively lower the rates of maternal mortality due to issues brought on by shifting the risk factors. this research will risk factor analyse the amount of maternal health risk intensity using classification approach while applying techniques of machine learning. Along with age of the person, other factors should also be monitored during pregnancy such as breathing rate, pulse, blood oxygen level, body temperature, systolic and diastolic blood pressure [9]. In machine learning, the algorithms are "trained" in order to search through vast amounts of data for the purpose patterns and features to draw conclusions and make predictions based on newly available data. An algorithm at a higher level will generate predictions and conclusions that are more accurate because it analyzes more data. Health Risk Analysis for Mothers This thesis discusses the useof EDA with machine learning. Analyze using these details in this case. In t h i s study, wetrain it using machine learning, then show the outcomes. Five algorithms that combined machine learning and EDA were utilized to perform this task. The Gaussian Naive Bayes, Xgboost, Random Forest, Support Vector Machine (SVM) along with Decision Tree are these five algorithms. These algorithms can create the best and most efficient outcomes[6]. It is the responsibility of healthcareproviders to make sure that AI applications offer practical technologies to support patient care. Due to the possibility of using applications that did not existthroughout their study, medical students must acquire the necessary knowledge and abilities about AI applications in medicine [11]. Empathy and compassion, they cannot replace human doctors. Additionally, since AI is undoubtedly not the conventional method, it is natural for patients to not put their full trust in it right away[5]. The studies says, some medical professionals particularly radiologists view artificial intelligence as a threat to their careers[13]. Although AI has a lot of potential in the healthcare industry, there are still some obstacles that must be overcome. Ethics, law, and regulations must all be carefully considered when integrating AI into clinical operations. Concerns over dataprivacy and security, as well as problems with the openness and interpretability of AI algorithms, must be carefully addressed[14]. The aim of this research is to examine and forsee patients with often diseases. This can be achieved by modern approaches of machine learning, making sure that the categorization correctly identifies those who have ailments.

A lot more uses for AI are still to come, especially in light of the expanding demands of patients. The perspective of AI and its application in healthcare environment is amazing, but more research and studies are urgently needed to fully establish.

Since many diseases may leads to the common type of symptoms so detecting them can be a tough task. The suggested system predicts maternal health risk using machine learning methods called Multinomial Naive Bayes, Random Forest Classifier, and K-Nearest Neighbors [16].

II. LITERATURE REVIEW

We are focusing on maternal health risks in this area, and work has already been done on this topic by numerous people; here just the emphasis is on the literature Review given below.

The issue of pregnant women's risk level was noted Ahmed et al. observed the concern regarding the risk level of pregnant women in their research titled IoT Based Risk Level Prediction Model for Maternal Health. The solution was devised integrating mining of data, some machine learning algorithms along with a statistical approach, and a predictive model within a risk factor analyzer to demonstrate the functionality of the DT algorithm.

Ram Neiger et al. highlighted the concern of enduring maternal complications stemming from pregnancy in their paper titled, Long-Term Effects of Pregnancy Complications on Maternal Health. To enhance women's well-being and mitigate these risks, both women themselves and their healthcare providers must be cognizant of these potential complications.

In their paper title, Early Prediction of Severe Maternal Morbidity, presented at the Ibero- American Conference on Artificial Intelligence (November 2016), Their proposed solution involves leveraging specific techniques to develop a tool aimed at identifying or classifying the risk level of patients with SMM. The objective is to ensure timely and appropriate attention for each patient based on the determined risk level, utilizing algorithms such as KNN, NN, DT,ANN, and LR.

Williams et al. in Paper The Effect of Maternal Obesity on the Offspring determine the Risk of maternal obesity and came up with the solution which expected that these approaches will help decrease risk in fetus, infants and mother and these decreased risk will be salient for someone's life.

Akhan Akbulut et al. in his paper, fetal health status prediction based on maternal clinical history using machine learning techniques identified around 60– 70% of anomalies are detectable through ultrasonography, leaving the remaining 30–40% for post-childbirth diagnosis. Different machine learning were employed for this purpose.

Subhash Mondal et al. in his paper Machine learning based maternal health risk prediction model for IoMT framework researched the IoT technology is being used in this study to track and forecast hazards associated with pregnancy. IoT devices gather real-time health data, which isthen machine learning analysed and the Random Forest Classifier is used to achieve an accuracy of 93.14%. The prediction model is used by an Android app to lower rates ofmother and infant mortality and enhance maternal health maintaining the integrity of the specifications.

Hursit Burak MUTLU et al.in his research paper "Prediction of Maternal Health Risk with Traditional Machine Learning Methods", emphasised The assessment of risk intensity inpregnancies when pre-existing medical disorders may deteriorate maternal health is the main focus of this study. Toevaluate maternal risk health, machine learning technique analyse medical data including the age of person, heart rate, blood oxygen levels, blood pressure, and temperature of the body. The goal of theresearch is to enhance maternal health outcomes and enable early detection of pregnancy-related problems.

There is a favourable correlation between the anxiety and depression levels of teenage children and the discomfort experienced by their moms. The research also demonstrates that when teens, especially female teens, take on greater caregiving responsibilities (both practical and emotional filial obligations) as a result of their mother's unhappy marriage, their mental health deteriorates more. The study concludes by noting that parentification—the phenomenon inwhich children take on caregiving responsibilities—occurs often in low-income homes headed by single mothers. It alsoemphasises the need of offering these families family therapy and practical assistance to help mitigate these challenges.

D.E. Gkotsis et al. in his paper "Machine learning and artificial intelligence for medical physicists :the importance of contiguous self learning", emphasized that Because AI and ML are transforming medical physics, medical physicists must constantly study for themselves in order to keep up to date. Comprehending these technologies is essential for enhancing patient care, as they have an effect on personalised medicine, treatment planning, and diagnosis. Competency, flexibility, and lifetime learning are all improved via self- learning. To sum up, medical physicists must embrace self-learning in order to stay abreast of the advancements in AI and ML, which will improve patient outcomes and the discipline.

All of these research demonstrate the importance of technology and machine learning while addressing a numberof important topics pertaining to maternal health and pregnancy-related hazards. Topics covered in the research include maternal obesity concerns, long-term implications of pregnancy difficulties, machine learning-based prediction models for mother health. These results highlight how important it is to keep current with new developments in order to enhance patient care and outcomes related to maternal health.

III. PROPOSED METHODOLOGY

A. Data Pre-Processing

This step involves a dual process comprising outlier removal and feature selection. Here's a breakdown of both procedures:

Outliers Removal[1]: Outliers are the extreme values that are distinctly different from majority of data. The algorithms of machinelearning are often influenced when a value of an variable falls outside its anticipated range. These anomalies typically arise from measurement or execution errors, causing deception to machine learning models and resulting in various issues during training, ultimately compromising the effectiveness of the algorithm. Multiple methods exist to eliminate outliers. The Maternal Health

Dataset contained certain outliers, and an effort was made to eliminate them. The most important features for a particular machine learning algorithm served as the basis for eliminating outliers. The data collection process. These incredibly high values are very remote from other findings.Anomalies can deceive machine learning models, causing several complications during training and resulting in a less efficient algorithm. Various methods exist to address outlier-related challenges. Within the Maternal Health Dataset, specific outliers were identified and subsequently removed. The elimination process was centered around excluding outliers based on the most crucial features relevant to a particular machine learning algorithm. Following this procedure, the dataset's instances are expected to decrease.

Feature Selection[1]: The data that is now being collected is highly dimensional and information-rich. Finding a dataset with manu number of features is casual . Feature selection is a method for choosing the most noticeable features out of a set of n-features. Feature selection is crucial for the following reasons:

1) The required training time of a model grows exponentially as the features in it increases.

2) A higher number of characteristics also increases the risk of over fitting.

3) The feature selection method utilized in this work is Select From Model.

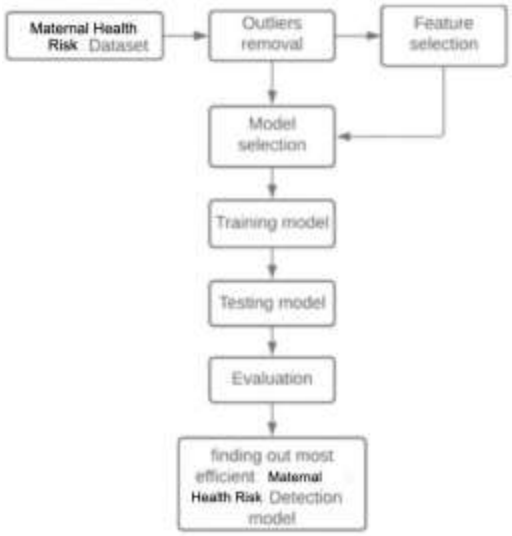


Fig.1.:Proposed Methodology

The priority attribute threshold is the basis for the feature selection method Select From Model select features. By default, this threshold is mean. Subsequently, diverse machine learning models were trained using these chosen features, resulting in an enhanced efficiency compared to previous iterations.

B. Model Selection and Training

From the dataset, we'll generate both a training data and a testing data. The former will serve to train the model, while the test dataset will be employed to assess its performance. Throughout the testing phase, performance data will be collected, facilitating the subsequent model evaluation stage.

C. Model Evaluation

Assessing models is essential to pinpoint the optimal among our proposed options. Following the training and testing of all models, the subsequent step involves evaluating which machine learning model best fits the given problem. This assessment involves gauging themost suitable machine learning model based on various performance indicators. These performance measurements serve as benchmarks to gauge improvements in the models. The selection of metrics is crucial to ensure an accurate evaluation of the machine learning model.

Confusion Matrix : Our aim is to address a classification-oriented problem. Among the widely employed techniques for evaluating classification-based machine learning models, confusion matrices stand out. They offer a comprehensive snapshot of the efficacy of machine learning models by assessing their performance through numerical counts, making them one of the most straightforward performance indicators. Both binary and multiclass classifications make use of this method. The upcoming section (in Fig.) elucidates the specifics of the confusion matrix pertaining to binary classification.

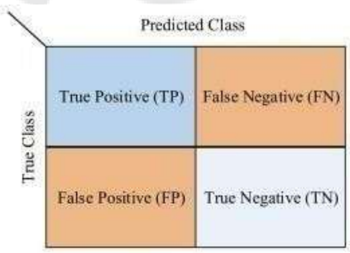


Fig.2.: Confusion Matrix

Confusion matrix is a two-dimensional table that has four sections. The following explains each of the four confusion metrics components:

True Positivity: A machine learning system is effective at classifying positive cases as positive. The count of cases that are expected to belong to Label 1 and actually do so appears in the true positive section. It is sometimes referred to as sensitivity and is reported as the True Positive Rate (TPR), to measure it get the ratio of true positives to actual positives.

True Negative: A machine learning algorithm is effective at classifying negative situations as negative. The count of instances that are expected to belong to Label 0 and actually do so appears in the true negative section. Specificity, also known asTrue Negativity Rate (TNR), is the proportion of accurately anticipated negative samples to actual negative samples.

False Positive: This is an instance of inaccurate categorization problem prediction made by a model. This section includes a count of instances that are anticipated to belong to Label 1 but actually fall under Label 0. FPR or False Positive rate is the ratio of falsely anticipated positive outcome to truenegative ones.

False Negative: This is an instance of inaccurate categorization problem prediction made by a model. This section includes a count of cases that are anticipated to belong to Label 0 but actually fall under Label 1. The (FNR)is the way to measure it. The proportion of positive instances that are expected to be negative compared to actual positive cases is known as the false positive rate (FNR).

Accuracy: This will determine how well the ML model is doing. Correct forecasts are the foundation of accuracy. Therefore, it is the ratio of accurate predictions to all other guesses.

Precision: Precision takes into account the accuracy of classes that were correctly predicted. The precision ratio measures how often positive events are properly anticipated compared to all positive events.

Recall: Sensitivity of confusion matrix is also known as recall.

F1-score: Another performance is F1- Score. F1-score is result of recall and precision's harmonic mean.

AUC-ROC Curve: Area Under Curve (AUC) - Receiver operating characteristic (ROC) curve is a crucial tool for analysing how well a classification problem is performing. When it comes to the evaluation of models, it is one of the most crucial performance metrics. AUC measures separability, whereas ROC is a probability curve. AUC is more valuable in better machine learning models than in inferior ones.

Its value ranges from 0 to 1. The ROC curve represents the relationship between the TruePositivity Rate and the False Positivity Rate. Let's saythe AUC for a machine learning-based model is 0.8, which indicates that there are 80% possibilities the model can tell the difference between label 0 and label 1 classes.

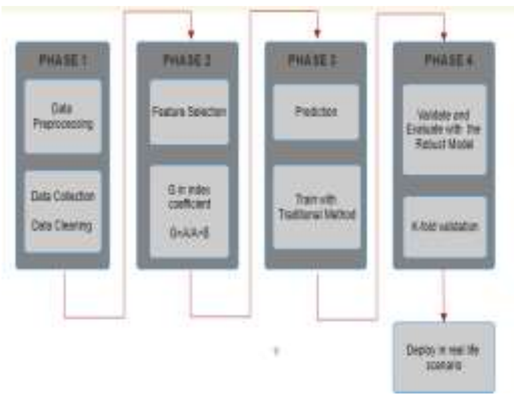


Fig.3.: System Model

The development of a reliable model to forecast maternal health risk is the main emphasis of this section. There are four phases to this project. The problem is first defined, and to solve it, a sample from the library of UCI machine learning is chosen, and the necessary pre-processing is carried out on it. Important characteristics in the imported dataset should be emphasized, therefore in the next phase,we use the Ginni index to perform feature selection on it and identify the standout aspects of our dataset. We train and test it using the conventional Machine Learning technique in the third phase. In the last phase, we contrast the performanceof the model with K-fold cross validation technique with that of the conventional machine learning technique.[2].

When a model is evaluated on a fresh, independent dataset The resilience of a system, much like the original one, can serve as a gauge for its quality. A robust algorithm,to rephrase, is one that displays a testing error closely aligned with its training error. It's crucial that the algorithmswe craft for machine learning exhibit resilience against worst- case noise, given their application in increasingly intricate tasks and on progressively noisier datasets. Even when our focus isn't solely on pure statistical analysis, integrating resilience into learning systems remains critical. By equipping our deep learning models with robustestimators, we can shield them from irrelevant or potentially misleading data. Recent research has highlighted the impact of adversarial perturbations on machine learning algorithms, illustrating how even minor input alterations undetectable byhumans can entirely alter the model's output. Given the significant security threats faced by real-world applications, formally evaluating the robustness of machine learning models becomes imperative.[2]

We initially evaluate execution of the model over a range from 0 to 10 folds to determine its robustness. We get our results for different scenarios - best, average, worst scenarios after applying the ten folds. The feature selection model is then applied, and the dataset is then trained. The output is made sturdy and reliable once we determine the average across all situations.

IV. Results

In our study, we systematically evaluated five different algorithms of machine learning, namely Support Vector Machine (SVM), Logistic Regression, Decision Trees Classifier k-Nearest Neighbors (KNN) and XGBoost, utilizing a dataset. We constructed two types of models for each algorithm: one employing a traditional approach, and another incorporating k-fold cross-validation methodology. Through rigorous analysis and testing, we obtained comprehensive results that highlighted the performance of these algorithms under varying conditions. The findings from these evaluations provide valuable insights into the effectiveness of these models, shedding light on their respective strengths and weaknesses

SVM:

With traditional model the Accuracy achieved is 0.5960591133004927, Precision is 0.6454092298884338, Recall is 0.596059113300492 , F-beta Score is 0. 5 7 0 4 7 3 6 1 5 0 5 6 8 2 3 8 a n d R O C AU C S c o r e :0.795212696510777

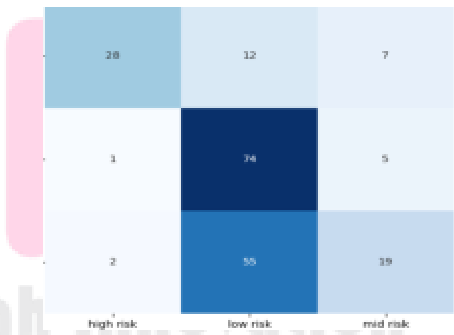


Fig.4.: Confusion Matrix of Traditional SVM

With K fold cross validation Accuracy achieved is 0.5650887573964497, Precision is 0.590233747432748, Recall is 0.5650887573964497 F-beta score is 5 5 6 5 2 4 8 0 5 7 5 9 1 5 4 4, ROC AUC Score is 0.7513558464836726.

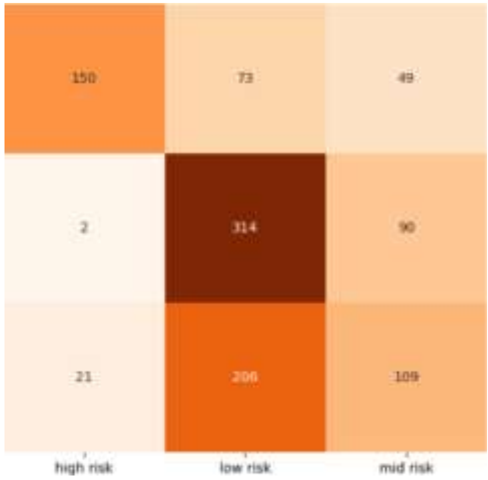


Fig.5.:Confusion Matrix of SVM(K-fold Cross Validation)

LOGISTIC REGRESSION:

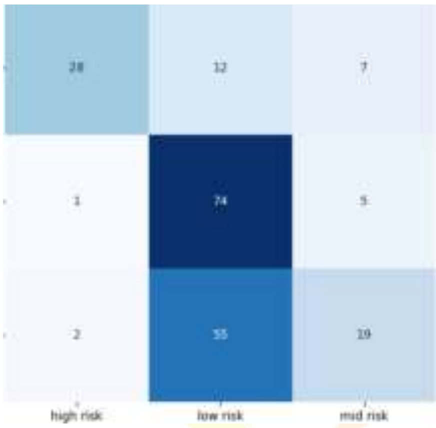


Fig.6.:Confusion Matrix of Traditonal logistic regression

With traditional model the Accuracy achieved is 0.645320197044335, Precision:is 0.6501490795955406, Recall is 0.645320197044335, F-beta Score is 0.6238102264582934

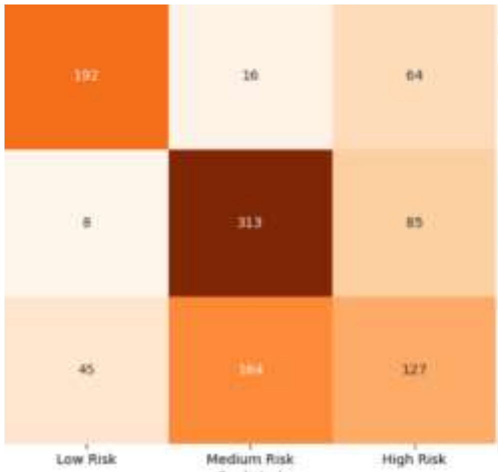


Fig.7.:Confusion Matrix of Logistic (K-Fold Cross Validation

With K-fold cross validation Accuracy achieved is 0 . 62327416102 , Precision is 0.6168960406, Recall is 0.6232741617357002 F-beta Score 0.6190627832821838 ROC AUC Score: 0.792420884009422.

K-Nearest Neighbour:

With traditional model the accuracy achieved is 0.6847290640394089, Precision is 0.8209751980005,F-beta Score is 0 . 6 8 2 9 5 1 0 5 9 2 1 5 7 11 4 and ROC-AUC S c o r e : 0.9137107402133703 while with K fold cross validation Accuracy is 0 . 8274161735700197 , Precision is 0.8326246342721869, Recall is 0 . 8 2 7 4 1 6 1 7 3 5 7 0 0 1 9 , F - b e t a S c o r e 0.8274161735700197.

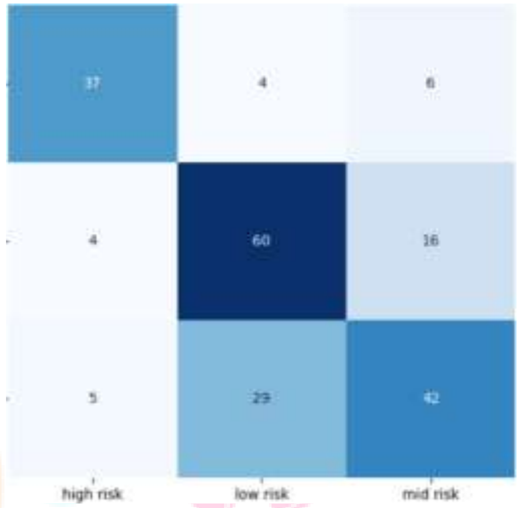


Fig.8.:Confusion Matrix of Traditional KNN- Classifier

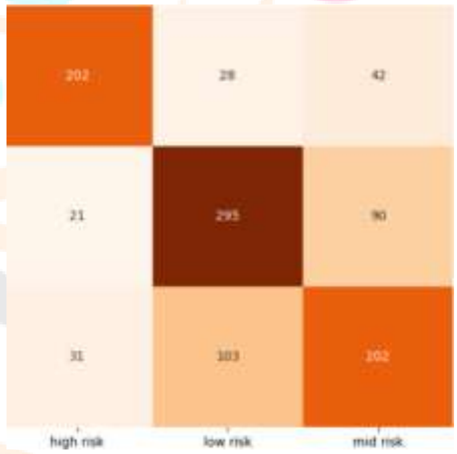
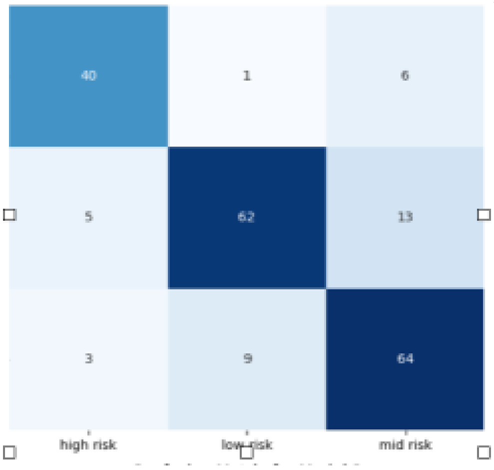


Fig.9.: Confusion Matrix of KNN-Classifier(K- fold cross validation)

Decision Tree Classifier:

With traditional model the Accuracy achieved is 0.8177339901477833, Precision is 0.8209751980005, Recall is 0.8177339901477833, F-beta Score is 0 . 8 1 7 4 2 9 5 1 6 5 4 1 9 0 7 1 a n d R O C AU C S c o r e :0.9137107402133703 while with K fold cross validation Accuracy is 0.827416173700, Precision is 0.83262463427, Recall is 0.8274161735700197, F-beta Score 0.8274161735700, ROC AUC Score: 0.82715869884268.


40
1
6
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high risk
low risk
mid risk

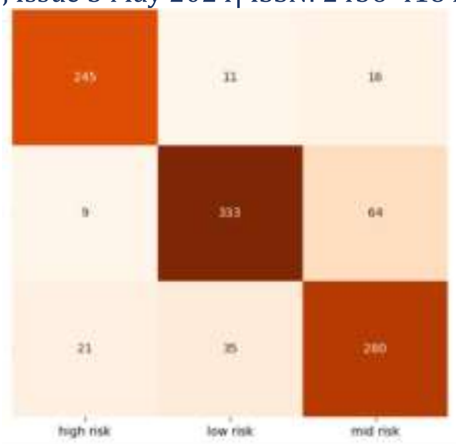
high risk
low risk
mid risk

Fig.10.: Confusion Matrix of Traditional Decision Tree

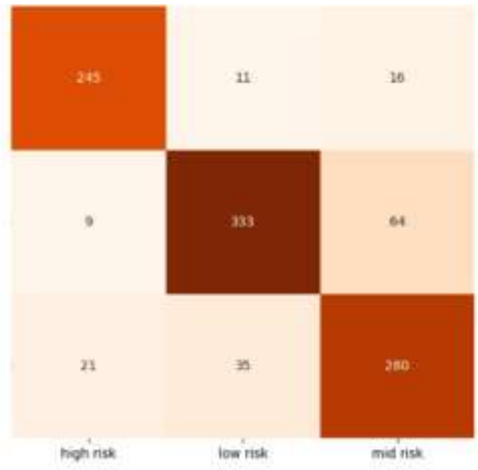

Fig.11.: Confusion Matrix of Decision Tree Classifier(K-Fold Cross Validation)

XG Boost Classifier:

With traditional model the Accuracy achieved is 0.842364532019704,Precision is 0.84329624530553, Recall is 0.8423645320197044, F-beta score is 0.84232331216787, AUC ROC Score is 0.950291063400 while with K fold cross validation Accuracy is 0 . 8461538461538461 , Precision is 0.8485044982304977, Recall is 0 . 8461538461538461 F- beta Score 0.8461596185671836 ROC AUC Score is 0.9508623093716141.

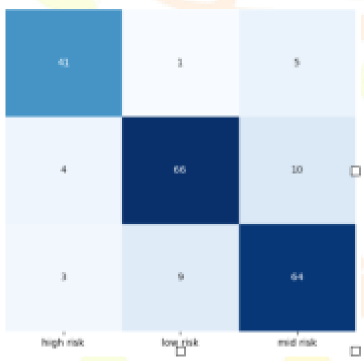

Fig.12.: Confusion Matrix of Traditional XGBoost

Fig.13.: Confusion Matrix of XGBoost(K-fold cross validation)

Below are the performance metrics using traditional algorithm along with K-fold cross validation:

Table 1: Percentage Split

Classifier	Accuracy	Precision	recall	Fbeta	ROC
SVM	0.596	0.645	0.596	0.5704	0.795
Logistic regression	0.645	0.6501	0.645	0.623	0.812
Decision tree	0.817	0.8209	0.817	0.8174	0.913
KNN	0.684	0.606	0.684	0.682	0.852
XGBOOST	0.842	0.843	0.842	0.8423	0.9502

Table 2: K-fold cross validation

Classifier	Accuracy	Precision	recall	Fbeta	ROC
SVM	0.565	0.5902	0.565	0.556	0.751
Logistic regression	0.623	0.616	0.623	0.619	0.792
Decision tree	0.827	0.832	0.827	0.8271	0.919
KNN	0.689	0.691	0.689	0.6894	0.855
XGBOOST	0.846	0.848	0.846	0.8461	0.9508

V. CONCLUSION AND FUTURE SCOPE

We use a thorough methodology in our suggested model to improve the caliber and dependability of our findings. We start by applying cross-validation techniques to convert raw data, which is produced via a straightforward percentage split, into a more reliable and consistent dataset. This crucial stage makes sure that our model is properly assessed and tested to handle a range of situations. Our feature selection procedure is the core of our data transformation, and the Gini index is essential to it. This method gives us a clear picture of which factors have a substantial impact on the result by helping us to recognize and preserve the most significant aspects in our data. This makes our approach more streamlined, effective, and equipped to deal with the complexity.

Our study has demonstrated the potential of leveraging predictive modeling techniques to assess maternal health risks. Through the integration of various factors such as demographic information, medical history, and lifestyle data, we have developed a robust model capable of identifying women at higher risk for complications during pregnancy and childbirth. Our findings underscore the importance of personalized risk assessment in maternal healthcare, as it enables targeted interventions and resources allocation to mitigate adverse outcomes.

Furthermore, our research highlights the need forcontinuous refinement and validation of predictive modelsin maternal health. As new data becomes available and healthcare practices evolve, updating and improving these models will be essential to ensure their accuracy and effectiveness in clinical settings. Collaboration between researchers, healthcare providers, and technology experts is critical to harnessing the full potential of predictive analytics in improving maternal outcomes.

By addressing these challenges and opportunities, future research endeavors have the capability to significantlyadvance our perception of maternal health risks and improve results for mothers and their children worldwide.

This approach's main benefit is its capacity to transform subpar outcomes into inspiring success tales. The results of our early work using raw data and conventional algorithms were not at all acceptable. We started the process of preparing the data after realizing there was space for improvement. The findings showed a notable improvement over the conventional approaches after we included feature selection. But, as every conscientious researcher is aware, there's always space for improvement. Even though we are now achieving better outcomes than we could with conventional algorithms and raw data, we are dedicated to never stopping trying to become even better.

In our paradigm, evaluating performance is a multifaceted endeavor. It includes a number of fields, suchas operational research. To provide a more comprehensive knowledge of our model's capabilities, we evaluate its performance here using a combination of two or three parameters. Specifically, the Weighted Sum of Absolute Weights (WSAW) score shows promise as a powerful measure of the robustness and accuracy of our model. While the outcomes of our algorithm are certainly quite good, we think that investigating other approaches from the operational research domain might improve the performanceof our model even more. Future research will thus explore these unexplored areas in an effort to find fresh ideas and perspectives that might eventually result in an improved model.

To sum up, we are on a continuous learning path where feature selection, data pretreatment, and performance evaluation across several domains come together to produce a solid and trustworthy model. The quest of excellence continues to be at the center of our research endeavors as we expand our horizons and improve our methodology.

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