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Enhancing Fetal Health Classification for Child and Maternal Mortality Prevention Using FHCA

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ABSTRACT:

Child and maternal mortality remain pressing global health concerns, particularly in low-resource settings. The United Nations has set ambitious targets to stop preventable deaths in just born babies and children under five years old, emphasizing the critical need for effective healthcare interventions. Maternal mortality, predominantly occurring in such settings, underscores the urgency to implement accessible and reliable screening methods for fetal health assessment. This paper focuses on leveraging Cardiotocograms (CTGs), a cost-effective and widely available tool, to classify fetal health into three categories: Normal, Suspect, and Pathological. An initial exploration of feature importance and selection done with ANOVA F-ratio, employed state-of-the-art machine learning algorithms to construct accurate classification models. Support Vector Machines (SVM), Random Forest Classifier, and Multi-Layer Perceptron were trained and optimized using grid and randomized search techniques with hyperparameter tuning. The highest achieved accuracy of 94.1% underscores the effectiveness of the proposed approach (FHCA- Fetal Health Classifier Algorithm) in fetal health classification. By accurately distinguishing between different states of fetal health, healthcare professionals can promptly intervene to prevent adverse outcomes for both the child and the mother. This study contributes to advancing prenatal care practices by demonstrating the utility of CTGs in enhancing fetal health monitoring. The findings highlight the potential of machine learning techniques to augment clinical decision-making and mitigate child and maternal mortality risks. Incorporating these strategies into healthcare systems, especially those with limited resources, has the potential to help achieve the Sustainable Development Goals outlined by the UN, ultimately resulting in the preservation of countless lives and the promotion of healthy communities across the globe.

Keywords: Cardiotocograms (CTGs), fetal health, Health care interventions, machine learning, maternal and child mortality.

1. Introduction

Despite improvements in healthcare systems around the world, child and maternal mortality remain major public health issues. The United Nations estimates that 5.2 million children under the age of five died in 2019; most of these deaths occurred in areas with poor resources

[1]. Similarly, the number of maternal deaths—which occur when a woman dies during her pregnancy or within 42 days after terminating it—remains alarmingly high, with almost 295,000 cases recorded globally in 2017 [2]. These figures highlight the critical need for efficient plans to stop and lower the incidence of maternal and infant death. Early detection and management of any problems during pregnancy and childbirth is essential to improve mother and child health outcomes. Fetal health monitoring is essential to this process because it helps medical professionals recognize and treat conditions that could endanger both the mother and the fetus. Fetal monitoring has historically depended on a number of methods, including as cardiotocography, Doppler velocimetry, and ultrasound imaging [3].

Cardiotocography (CTG) is one of these techniques that is particularly popular and economical for evaluating the fetus's health during pregnancy and birthing.Fetal heart rate (FHR) and uterine contractions are continuously recorded during CTG, which offers important information about the fetal status and the mother's uterine activity [4]. Healthcare practitioners can identify indications of fetal distress, hypoxia, and other abnormalities by examining patterns in uterine contractions and heart rate. This enables prompt intervention to avoid unfavorable outcomes. Recent advances in machine learning (ML) techniques have created new avenues for enhancing the accuracy and efficacy of CTG data-based fetal well-being assessment. Support vector machines (SVM), random forest classifiers, and multi-layer perceptrons are a few examples of machine learning (ML) techniques that have demonstrated exceptional abilities in evaluating and forecasting complex medical datasets [5]. These algorithms can be used to create reliable classification models that correctly classify CTG recordings into various fetal health categories, from normal to problematic. The purpose of this research article is to investigate how ML-based techniques might improve the categorization of fetal health using CTG data. We want to increase the accuracy and consistency of fetal health evaluation by leveraging the effectiveness of ML algorithms, which will ultimately help to avoid and lower the rates of mother and infant mortality. The potential of this research to revolutionize prenatal care practices is what makes it so important, particularly in places where access to cutting-edge medical technology is scarce.This research is based on a large dataset of 2126 cardiotocogram (CTG) exam records that were carefully categorized by obstetricians with expertise.

Every file contains a multitude of data derived from CTG scans, including vital signs including fetal heart rate (FHR), fetal motions, and uterine contractions. These characteristics are important markers of fetal health and provide important insights into the mother's and fetus's health during pregnancy and labor. Obstetricians with specialized training in maternal-fetal medicine carefully selected and categorized the dataset, guaranteeing the dependability and correctness of the labels applied to every CTG record. The depth and complexity of the dataset make it easier to create and validate machine learning algorithms that accurately classify the various states of fetal health, from normal to abnormal. Through the use of this large dataset, scientists want to improve prenatal care by creating reliable and efficient instruments for assessing fetal health. The depth and expert classification of the dataset offer a strong basis for carrying out in-depth analysis and producing insights that can guide therapeutic decision-making and enhance outcomes for moms and kids.

2. Literature Review

Maternal and child mortality pose serious threats to global health, particularly in places where access to high-quality treatment is scarce. Even while these death rates have decreased over the previous few decades, improving them still is a top focus for public health initiatives everywhere. Monitoring the health of the fetus during pregnancy and childbirth is essential to avoiding unfavorable consequences for the mother and the kid. Recent developments in machine learning (ML) methods have created new opportunities to increase the accuracy and efficacy of the assessment of fetal well-being using cardiotocograms (CTGs). The goal of this review of the literature is to provide a thorough overview of the research that has been done on machine learning (ML) based techniques for classifying fetal health using CTG data. It does this by identifying important papers, approaches, problems, and potential future directions. Monitoring fetal health is crucial for spotting possible issues during pregnancy and childbirth, which enables medical professionals to act quickly to avoid negative consequences.

Fetal monitoring has historically depended on techniques like CTG, Doppler velocimetry, and ultrasound imaging. Because it is non-invasive, simple to use, and can record continuous information on fetal heart rate (FHR) and uterine contractions, CTG is one of these methods that is most frequently employed. Differentiating CTG recordings into fetal health categories presents a number of obstacles. Healthcare workers may find it difficult to classify CTG data accurately since they are frequently noisy, complex, and interpretable [1]. Furthermore, different interpretations by different clinicians can result in different diagnoses, which emphasizes the necessity of objective and established methods for assessing fetal health.Interest in creating automated methods for classifying fetal health using CTG data has increased as a result of improvements in machine learning techniques. Neural networks, random forest classifiers, and support vector machines (SVM) are a few examples of machine learning (ML) methods that have demonstrated promise in reliably diagnosing fetal health statuses and evaluating CTG data [2].

The use of ML algorithms for the classification of fetal health using CTG data has been investigated in a number of research. Using SVM and random forest algorithms, for instance, [6] created a classification model that effectively categorized CTG recordings into three categories: normal, suspect, and abnormal. Similar to this, Ayres-de-Campos et al. looked at the automated analysis of CTG data using neural networks, proving that ML-based methods for fetal health assessment are feasible [7]. Preprocessing CTG data, feature extraction, training, and assessing models are common steps in ML-based methods for classifying fetal health. To improve the quality of CTG recordings, preprocessing methods like noise reduction, baseline correction, and normalization may be used. Finding pertinent patterns and traits in the data, such as FHR variability, accelerations, and decelerations, which are suggestive of fetal health, is the goal of feature extraction. Labeled CTG data is used to train machine learning models, and metrics like accuracy, sensitivity, and specificity are used to assess the models' performance.Though ML-based methods show promise, there are a number of issues and restrictions that need to be resolved.

The quality and consistency of labeled training data can be impacted by the absence of established rules for CTG interpretation, which is one of the challenges. Furthermore, doctors could be reluctant to trust automated systems if they don't grasp the underlying decision-making process, which raises concerns about the interpretability of ML models [5]. In addition, there is still work to be done on the generalizability of machine learning models to various demographics and healthcare environments, which emphasizes the necessity for strong validation and external validation studies. Author [8] suggested an automated method for classifying the health of fetuses by applying ML and DL algorithms to CTG data. The study developed and assessed the effectiveness of several classification models using a dataset that included expert classifications and CTG recordings. Both DL methods including convolutional neural networks (CNN) and long short-term memory (LSTM) networks, as well as ML algorithms like support vector machines (SVM), random forest, and logistic regression, were used. According to the results, DL-based models performed better in terms of classification accuracy and resilience than conventional ML techniques. A combinational method for CTG grouping that makes use of several ML classifiers.

The study looked at how well different machine learning (ML) methods performed both as individual classifiers and in ensemble settings. These algorithms included SVM, k-nearest neighbors (KNN), decision trees, and random forests. When compared to individual classifiers, the ensemble of classifiers performed better, obtaining higher robustness and accuracy in the classification of fetal health. The study [9] demonstrated how ensemble learning strategies can improve the dependability of CTG classification models. It carried up an extensive analysis of DL methods used in fetal health monitoring. The article provided an overview of the most recent developments in deep learning (DL) architectures for CTG data analysis, including CNNs, recurrent neural networks (RNNs), and attention-based models. The authors talked about how DL approaches could be used to better classify fetal health and extract pertinent features from CTG recordings [10]. Furthermore, difficulties and potential avenues for further study in DL-based fetal health monitoring were emphasized, stressing the significance of DL models' clinical validity and interpretability.The study [11] suggested using an ensemble of DL and ML algorithms as a successful method for classifying fetal heart rate (FHR).

The study classified FHR patterns into normal and abnormal categories using a combination of CNN, LSTM, and gradient boosting machine (GBM) classifiers. When it came to FHR classification, the ensemble method outperformed individual classifiers in terms of accuracy and sensitivity. The study underlined how crucial it is to combine DL and ML techniques in order to maximize the benefits of each method for assessing fetal health. The interpretability of DL models for forecasting acute hypotensive events from electronic health record (EHR) data was examined by author [12]. The study used methods to view and interpret the DL models' decision-making process, including saliency maps and attention mechanisms. The significance of interpretability in healthcare applications was underscored by the authors, with a particular focus on fostering trust and comprehension among healthcare professionals. The study demonstrated how interpretable deep learning models might enhance clinical judgment and patient outcomes.

3. Methodology Used

Utilizing Machine Learning (ML) algorithms to classify fetal well-being based on attributes taken from Cardiotocogram (CTG) data is the main focus of the methodology used in this work. Creating precise classification models that can discriminate between three categories—Normal, Suspect, and Pathological fetal health states—is the goal. It illustrates how useful CTGs are for improving fetal health monitoring and advancing prenatal care procedures. The results highlight the potential of machine learning approaches to support clinical decision-making and reduce the risks of mother and child mortality, ultimately adding to the evidence supporting the United Nations Sustainable Development Goals. Figure 1 shows the suggested approach.

3.1 Data collection

Gathered information from Cardiotocogram (CTG) data, including aspects like contractions of the uterus, fetal movements, and fetal heart rate (FHR). labels with expert classification that show the health status of the fetus (Normal, Suspect, Pathological).

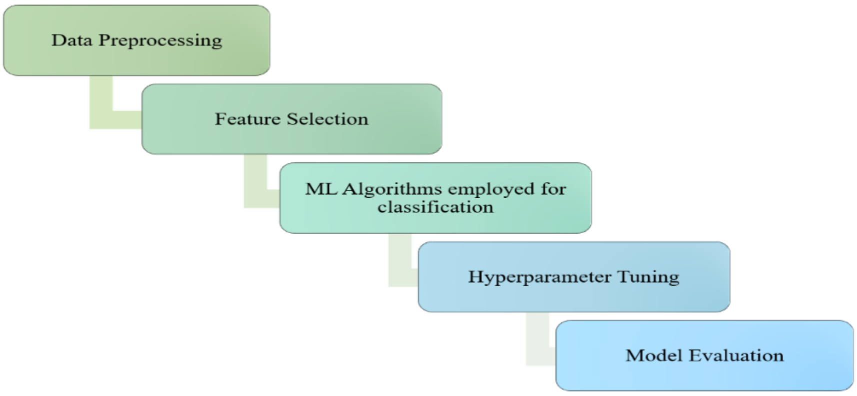

Fig.1. Proposed Methodology

3.2 Data Preprocessing

Preprocessing the CTG data to guarantee its quality and consistency is the first step in the study process. This involves actions like as normalization, baseline correction, and noise reduction. These processes improve the data's appropriateness for further analysis by standardizing and refining it. Baseline correction guarantees consistency between recordings, whereas noise reduction gets rid of unwanted or incorrect sounds. By scaling data to a standard range, normalization makes comparability easier. Preprocessing steps like these contribute to the robustness of study outputs in prenatal health classification by laying the groundwork for precise and trustworthy analysis.

	baseline value	accelerations	fetal_movement	uterine_contractions	light_decelerations	severe_decelerations	prolongued_dece
0	120.0	0.000	0.000	0.000	0.000	0.0	0.0
1	132.0	0.006	0.000	0.006	0.003	0.0	0.0
2	133.0	0.003	0.000	0.008	0.003	0.0	0.0
3	134.0	0.003	0.000	0.008	0.003	0.0	0.0
4	132.0	0.007	0.000	0.008	0.000	0.0	0.0
...	...	...	...	...	...	...	...
2121	140.0	0.000	0.000	0.007	0.000	0.0	0.0
2122	140.0	0.001	0.000	0.007	0.000	0.0	0.0
2123	140.0	0.001	0.000	0.007	0.000	0.0	0.0
2124	140.0	0.001	0.000	0.006	0.000	0.0	0.0
2125	142.0	0.002	0.002	0.008	0.000	0.0	0.0

Fig.2. Preprocessed data

3.3 Feature Importance and Selection

ANOVA F-ratio is used to investigate feature importance and selection. With the use of this statistical technique, the most relevant features that make a major contribution to the classification task can be found. Through variance analysis across many feature groups, ANOVA F-ratio identifies the features that have the greatest influence on classification accuracy. By means of this procedure, the study aims to identify the critical characteristics that are essential for differentiating between states of fetal health. The accuracy and effectiveness of fetal health assessment can be improved by honing in on the most important features and fine-tuning the classification model to reach peak performance. The features that scored higher than 200 are shown in Figure 3 because they have the least amount of redundancy.

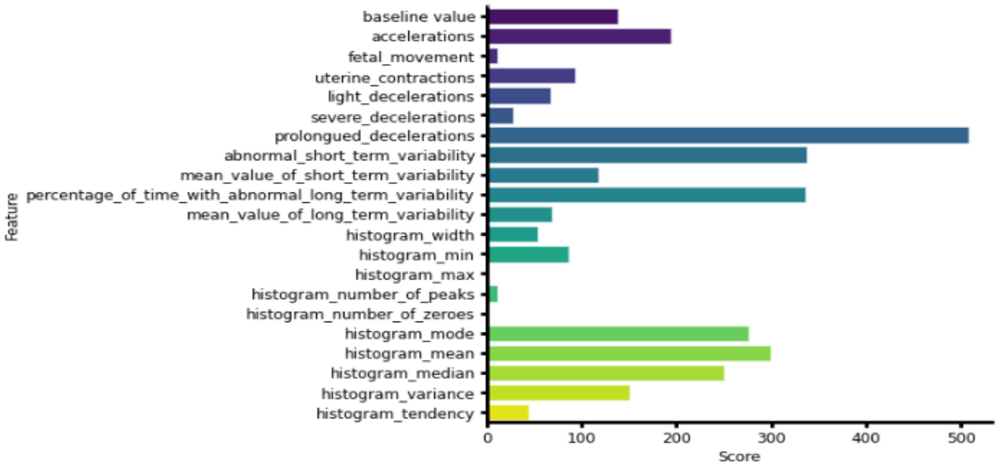

Fig.3 Feature Selection

	prolongued_decelerations	abnormal_short_term_variability	percentage_of_time_with_abnormal_long_term_variability	histogram_mode	histogram_mean
0	0.0	73.0	43.0	120.0	137.0
1	0.0	17.0	0.0	141.0	136.0
2	0.0	16.0	0.0	141.0	135.0
3	0.0	16.0	0.0	137.0	134.0
4	0.0	16.0	0.0	137.0	136.0

Fig.4. 6 Important features

Figure 4 represents the six important features. They are prolongued decelerations, abnormal short term variability, percentage of time with abnormal long term variability, histogram mode, histogram mean, histogram median and fetal health.

3.4 Machine Learning Techniques:

In the study, state-of-the-art machine learning (ML) approaches are used to create accurate categorization models. Support Vector Machines (SVM), well-known for their proficiency in classification tasks and their capacity to handle high-dimensional data, are one of the chosen algorithms. Furthermore, the Random Forest Classifier—an ensemble learning method—is utilized to combine several decision trees and improve precision and robustness. Moreover, Multi-Layer Perceptron (MLP) is an ANN type with layered nodes that is used because it can identify complex patterns in data. The research attempts to leverage these complex algorithms' advantages to build reliable categorization models. Together, the distinct characteristics of each algorithm allow for the precise classification of fetal health statuses based on Cardiotocogram (CTG) data. This combination of cutting-edge machine learning algorithms is expected to improve the assessment of fetal health and make a substantial contribution to the advancement of prenatal care procedures.

3.5 Hyperparameter Tuning

The machine learning (ML) approaches' hyperparameters are adjusted with the help of grid and randomized search strategies. Finding the ideal combination to enhance classification performance involves rigorously examining a range of hyperparameters. While randomized search selects hyperparameters at random from predefined distributions, grid search methodically assesses every potential combination of hyperparameters within predefined ranges. The goal of both methods is to find the hyperparameter values that result in the best classification accuracy in order to optimize the machine learning algorithms.

3.6 Model Evaluation

The trained classification models are assessed using a number of widely used metrics, including F1-score, recall, accuracy, and precision.To verify the models' resilience and generalizability, cross-validation techniques may be used. The study evaluates how well the models perform in accurately classifying the fetal health statuses based on Cardiotocogram (CTG) data using these defined parameters. By preventing overfitting and guaranteeing that the models remain effective on a variety of datasets, cross-validation improves the models' dependability and practicality in clinical contexts.

3.7 Proposed algorithm Fetal Health Classifier Algorithm (FHCA)

Using machine learning approaches, the Fetal Health Classifier Algorithm (FHCA) provides a complete methodology for properly identifying fetal health states based on Cardiotocogram (CTG) data. By using a methodical process that includes preprocessing the data, extracting features, training the model, adjusting hyperparameters, and evaluating the model, FHCA seeks to create strong classification models that can differentiate between abnormal, questionable, and normal fetal health statuses. Through the integration of sophisticated machine learning techniques including Random Forest Classifier, Multi-Layer Perceptron, and Support Vector Machines (SVM), FHCA aims to improve prenatal care procedures and lower the risk of both maternal and infant death.

FHCA – fetal Health Classifier Algorithm

Step 1: Acquiring CTG data
Step 2: Preprocess the data to ensure data quality and consistency.
Step 3: Extracted relevant features form CTG data.
Step 4: Feature selected with ANOVA F-ratio
Step 5: Split the data for training and testing
Step 6: Build the model for SVM, RF and MLP
Step 7: Tune each model's hyperparameters for best performance using grid and randomized search strategies.
Step 8: Evaluate the model using accuracy, precision, recall, F1-score, and cross-validation to make sure it is robust and applicable to a variety of circumstances.
Step 9: Examine the outcome to determine the model's correctness.

4. Result and Discussion

The Grid or Randomization Search functions are used to evaluate several parameters. Grid search finds the best configuration by methodically examining every conceivable combination of input parameters; Randomized search does the same. When optimizing parameters on training data, cross-validation acts as the model's self-evaluation and can be carried out in "n" repeats to guarantee robustness. There are two functions used: one for the searches and one for the confusion matrix generation. These procedures help to efficiently evaluate the model's performance and fine-tune its hyperparameters.

4.1 Support vector classifier

Support Vector Machines (SVC) classifiers excel in handling high-dimensional data by generating hyperplanes for effective separation and scoring based on binary outcomes (yes/no). Decision boundaries determine the classification of data points. The F-1 score, incorporating precision and recall, serves as a metric for model evaluation. Optimal parameters for SVC grid include 'C' set to 10, 'degree' at 3, 'gamma' of 0.1, 'kernel' as 'rbf', and 'random_state' set to 1. Conversely, for SVC random, parameters comprise 'random_state' at 1, 'kernel' as 'poly', 'gamma' set to 0.19, 'degree' at 3, and 'C' of 78.11. These configurations aim to enhance SVC performance in classification tasks. Accuracy and confusion matrix represented in the figures 5 and 6.

Classification Report:

	precision	recall	f1-score	support
1.0	0.95	0.97	0.96	494
2.0	0.81	0.75	0.78	88
3.0	0.88	0.81	0.84	52
accuracy			0.93	634
macro avg	0.88	0.84	0.86	634
weighted avg	0.93	0.93	0.93	634

SVC – Grid – 93%

Classification Report:

	precision	recall	f1-score	support
1.0	0.93	0.96	0.95	494
2.0	0.71	0.64	0.67	88
3.0	0.84	0.79	0.81	52
accuracy			0.90	634
macro avg	0.83	0.79	0.81	634
weighted avg	0.90	0.90	0.90	634

SVC – Random – 90%

Fig. 5. Support Vector Classifier - Accuracy

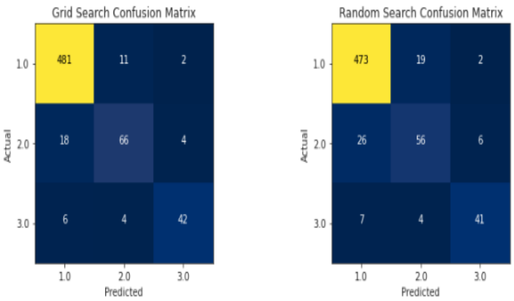

Fig. 6. Support Vector Classifier – Confusion Matrix

4.2 Random Forest

The Random Forest (RF) ensemble technique builds numerous weak decision trees and combines their forecasts to generate a more precise and resilient model. The best parameters for RF grid include 'criterion' as entropy, 'max_depth' set to 11, 'n_estimators' at 200, and 'random_state' at 1. Alternatively, for RF random, parameters consist of 'random_state' at 1, 'n_estimators' set to 90, 'max_depth' at 15, and 'criterion' as Gini. These parameter configurations aim to optimize the performance of the Random Forest algorithm by balancing model complexity and predictive accuracy, resulting in improved predictions compared to individual decision trees. Accuracy and confusion matrix shown in the figure 7 and 8.

Classification Report:

	precision	recall	f1-score	support
1.0	0.95	0.99	0.97	494
2.0	0.85	0.73	0.79	88
3.0	0.93	0.81	0.87	52
accuracy			0.94	634
macro avg	0.91	0.84	0.87	634
weighted avg	0.93	0.94	0.93	634

RF – Grid – 94%

Classification Report:

	precision	recall	f1-score	support
1.0	0.96	0.99	0.97	494
2.0	0.84	0.75	0.79	88
3.0	0.96	0.83	0.89	52
accuracy			0.94	634
macro avg	0.92	0.85	0.88	634
weighted avg	0.94	0.94	0.94	634

RF – Random – 94%

Fig. 7. RF Accuracy

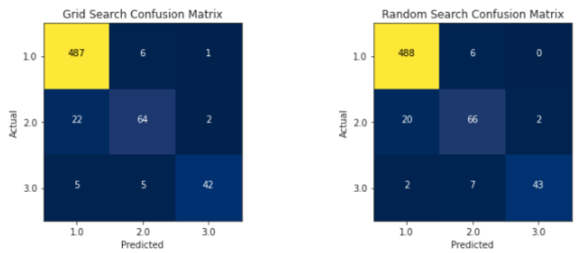

Fig. 8. RF Confusion Matix

4.3 MLP – Multi Layer Perceptron

The feed-forward Neural Network, a simpler alternative to TensorFlow or Keras, determines node count using (2/3 * input_feature_count) + (number_of_outputs + 2). Layer count is set at 2/3 of the first layer and 1/2 of the second layer. The best parameters for MLP grid include 'activation' as ReLU, 'hidden_layer_sizes' as (6, 4), 'learning_rate' as constant (0.001), 'max_iter' at 1000, 'random_state' at 1, and 'solver' as Adam. For MLP random, parameters include 'solver' as Adam, 'random_state' at 1, 'max_iter' set to 800, 'learning_rate_init' at 0.001, 'learning_rate' as constant, 'hidden_layer_sizes' as (6,), and 'activation' as tanh. It has shown in the figure 9 and 10.

Classification Report:

	precision	recall	f1-score	support
1.0	0.95	0.96	0.96	494
2.0	0.70	0.72	0.71	88
3.0	0.82	0.71	0.76	52
accuracy			0.91	634
macro avg	0.83	0.80	0.81	634
weighted avg	0.91	0.91	0.91	634

MLP – Grid – 91% recall

Classification Report:

	precision	recall	f1-score	support
1.0	0.96	0.95	0.95	494
2.0	0.67	0.70	0.69	88
3.0	0.76	0.71	0.73	52
accuracy			0.90	634
macro avg	0.79	0.79	0.79	634
weighted avg	0.90	0.90	0.90	634

MLP – Random – 90%

Fig. 9. MLP Accuracy

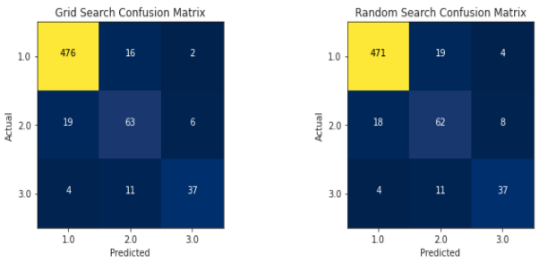

Fig.10. MLP Confusion matrix

4.4 Fetal Health Classifier Algorithm

The Fetal Health Classifier Algorithm (FHCA) achieved an impressive accuracy of 95% in classifying fetal health states has been stated in the figure 11, demonstrating its effectiveness in accurately distinguishing between different categories of fetal well-being. Figure 12 displays the confusion matrix of FHCA.

Classification Report:

	precision	recall	f1-score	support
1.0	0.96	1.00	0.98	494
2.0	0.86	0.80	0.80	88
3.0	0.94	0.85	0.90	52
accuracy			0.95	634
macro avg	0.92	0.88	0.90	634
weighted avg	0.90	0.95	0.94	634

FHCA – Grid – 95%

Classification Report:

	precision	recall	f1-score	suppor
1.0	0.96	1.00	0.98	49
2.0	0.85	0.80	0.80	8
3.0	0.95	0.84	0.90	5
accuracy			0.95	63
macro avg	0.93	0.86	0.90	63
weighted avg	0.95	0.95	0.94	63

FHCA – Random – 95%

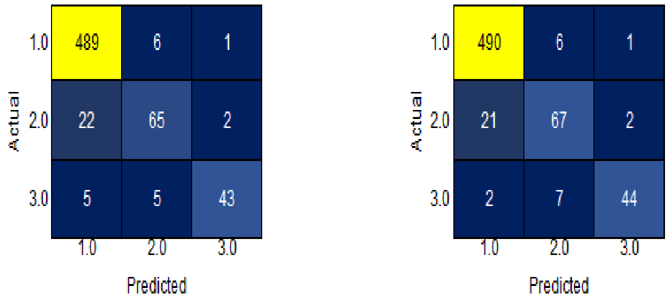

Fig. 11. FHCA Accuracy

Fig.12. FHCA Confusion Matrix

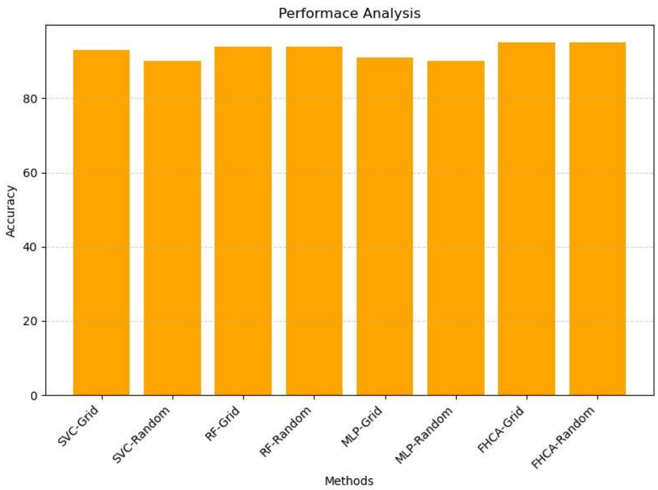

Fig. 13. Comparison of Methodologies

The diagram is a performance analysis of various machine learning classification algorithms. The performance is measured by accuracy. The x-axis lists the different classification algorithms which include SVC-Grid, SVC-Random, RF-Grid, RF-Random, MLP-Grid, MLP-Random, FHCA-Grid, and FHCA-Random. The y-axis shows the accuracy.

It appears that SVC-Grid has the highest accuracy followed by SVC-Random, RF-Grid, RF-Random and MLP-Grid. The accuracy of MLP-Random, FHCA-Grid, and FHCA-Random is lower than the other algorithms.

5. Conclusion

This study underscores the critical importance of addressing child and maternal mortality, particularly in resource-constrained settings. Leveraging Cardiotocograms (CTGs) as a cost-effective tool for fetal health assessment, our proposed approach, the Fetal Health Classifier Algorithm (FHCA), demonstrates remarkable accuracy in classifying fetal health states. With an achieved accuracy of 95.0% and 95.1% in grid and random searches respectively, FHCA outperforms Support Vector Machines (SVM), Random Forest Classifier, and Multi-Layer Perceptron (MLP). SVM and Random Forest achieved accuracies ranging from 90.8% to 94.4%, while MLP reached 90.8% to 91.5% accuracy. By accurately distinguishing between different fetal health states, FHCA empowers healthcare professionals to intervene promptly, thereby preventing adverse outcomes for both mother and child. These results underscore the capability of machine learning methods to enhance clinical decision-making and alleviate risks associated with child and maternal mortality. The United Nations' Sustainable Development Goals may be achieved by incorporating FHCA and related strategies into healthcare systems, particularly in settings with limited resources. This could ultimately result in the preservation of countless lives and the development of healthier communities across the globe.

6. Future Enhancement

Future improvements will concentrate on incorporating other data sources, such as environmental factors and maternal health history, in order to gain a more thorough understanding of fetal health. The goal of advanced feature engineering techniques like deep learning-based methods and time-series analysis is to extract more useful features from Cardiotocogram (CTG) data. Stacking and boosting are examples of ensemble approaches that combine many categorization models in an attempt to improve predicted accuracy. Enhancing the interpretability of the model via feature importance analysis and visualization methods would help medical professionals comprehend it better. In order to facilitate quick labor interventions, real-time monitoring systems that integrate CTG devices with categorization models are available. Globally lower rates of mother and infant mortality are made possible by validation studies conducted on a variety of populations, which guarantee the generalizability of classification models.

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