Optimized Machine Learning Approaches for Fetal Health Assessment Using PCA, LDA, and KPCA with Advanced Resampling Techniques

G Viswanath[1], D Chandini[2]
[1]Associate Professor, Department of CSE(AI & ML), Sri Venkatesa Perumal College of Engineering & Technology, Puttur, E-mail: viswag111@gmail.com, ORC-ID: https://orcid.org/0009-0001-7822-4739
[2]P.G Scholar, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, E-mail: chandinid07@gmail.com

To Cite this Article
G Viswanath, D Chandini, "Optimized Machine Learning Approaches for Fetal Health Assessment Using PCA, LDA, and KPCA with Advanced", Journal of Science Engineering Technology and Management Science, Vol. 03, Issue 04, April 2026,pp: 243-255, DOI: http://doi.org/10.64771/jsetms.2026.v03.i04.pp243-255
Submitted: 28-02-2026 Accepted: 01-04-2026 Published: 08-04-2026

Abstract: Proper examination of the well-being of the fetus is quite significant in preventing issues throughout the course of pregnancy and ensuring that the mother and the baby achieve optimal outcomes. The data of CTG that is mostly utilized to monitor the health of the fetus provides valuable data regarding the health of the fetus. Manual analysis is however time consuming and may give various interpretations. In this study the UCI Fetal Health Dataset is utilized in testing various predictive modeling techniques. These are PCA, LDA and KPCA. This is aimed at enhancing the accuracy of the diagnosis through a decrease in the number of dimensions. The class mismatch was overcome using both the SMOTE and SMOTEENN resampling techniques. Some of the machine learning models that were experimented on their performance included LR, XGBoost, RF, KNN, Support Vector Machine SVM, and Voting Classifier which is a combination of KNN and XGBoost. With SMOTE, PCA-XGBoost and PCA-Voting Classifier were able to get 98% accuracy, LDA-Voting Classifier got 98.1%, and KPCA-XGBoost got 96.6%. With the use of SMOTEENN, PCA-Voting Classifier scored 98.9%, LDA-KNN scored 98.9% and KPCA-Voting Classifier scored 97.9%. Also, the model was improved with LIME and SHAP to enhance the interpretability of the model by showing characteristics of CTGs that are important contributors. This ensured that there was clarity in clinical decision-making. A Flask-based framework was also developed in such a way that the end predictive system would be able to monitor the health of a fetus in real-time. These results indicate that the number of dimensions reduced and sophisticated resampling, explainable AI, and explainable machine learning significantly enhance the capacity to predict the health of a fetus, which is strong and accurate and offers automatic diagnostic assistance.

***"Index Terms** - Fetal health, cardiotocography (CTG), dimensionality reduction, PCA, LDA, KPCA, SMOTE, ensemble learning."*

1. INTRODUCTION

Pregnancy complications remain to be among the primary causes of mother and babies contracting diseases and dying, and fast diagnosis to ensure a proper diagnosis to enhance the health outcomes should be considered an important step. CTG is another diagnostic instrument that is mostly utilized to monitor the well-being of an unborn baby, by monitoring its heart rate and uteral motions. Although CTG is quite effective in the detection of fetal distress, it is difficult to agree on the interpretation of the CTG as various doctors have varied views. This may give rise to unnecessary procedures such as cesarean deliveries which do not have an advantage to the baby [1, 2]. Consequently, computer diagnostic techniques are receiving an increasing amount of consideration as a means of enhancing the accuracy and reducing errors in CTG analysis [3, 4].

Application of ML to detect fetal health has proved to be rather promising in transforming raw CTG data into usable information. Previous studies have indicated that the ML models outperform the conventional diagnostic tools in the prediction of fetal health issues. This is particularly in the case where it is applied with data preprocessing and resampling schemes to correct class mismatch [5, 6]. The high dimension and complexity of CTG datasets, however, complicate the provision of useful features and increase the performance of the model.

Some of the dimensionality reduction algorithms that can be utilized to simplify complicated datasets and yet significant data include PCA, LDA, and Kernel Principal Component Analysis (KPCA) [7, 8]. These techniques do not only reduce the price of a calculation, but they also enhance the representation of the features, which allows us to categorize fetal health outcomes more suitably.

Recent studies have demonstrated that PCA has the capability of reducing duplication of information, LDA has the ability to segregate classes more effectively and KPCA is able to discover nonlinear trends in medical information [9, 10]. This paper is based on these developments and the UCI Fetal Health Dataset is utilized in the comparison of the ability of PCA, LDA, and KPCA to predict fetal health. The core objective of the project is to develop a system, which will be automated and which will integrate dimensionality reduction with sophisticated machine learning systems to provide more accurate diagnoses, less interpretive variability, and provide obstetric care professionals with high-quality decision-support.

2. RELATED WORK

Follow up of the health of a baby has been a major area of concern since it directly influences the health of the mother and the baby. Historically, traditional CTG has been a clinical standard and its manual interpretation has been associated with a reduced specificity and inter-observer variability. This is the reason why better diagnostic support is made through ML and statistical approaches. Researchers are increasingly concerned with the dimensionality reduction and classification techniques in order to make predictions of fetal health more precise, efficient and comprehensible.

LDA is one of the methods that have been researched extensively and have been used to cluster fetal health issues using CTG data. LDA simplifies the distinction between classes and provides medical applications with a context to be comprehended. Mukherjee [10] discussed the extent to which it can correctly detect patterns in the health of a fetus and Gupta [11] discussed the predictive capability of discriminant methods and highlighted the usefulness of the predictive methods in making better predictions as to what will occur to a newborn. LDA is effective in linear cases, and nonlinear cases are poor with nonlinear data distributions, as present with CTG datasets.

More and more, KPCA is being applied to nonlinearity. Singh and Sharma [12] demonstrated that KPCA had the ability to extract nonlinear features and this feature simplified the classification of data related to the health of the fetus. In the same way, Das [13] used KPCA with ML models to improve the classification of fetal health by extracting more useful features. These studies claim that KPCA is capable of detecting latent patterns in CTG data that may not be available in more conventional linear techniques. PCA on the other hand has been applied frequently in the medical field to minimize the dimensions. Nguyen [14] applied PCA to categorize fetal health revealing that it is able to eliminate noise, redundancy of data yet retains the significant features to classify it correctly.

AI techniques to analyze CTG, not based on dimensionality reduction, have received a large amount of research. Chavez et al. [15] conducted an extensive review of the AI use in fetal tracking by highlighting the potential application of deep learning and hybrid solutions in reducing the number of errors that humans commit. In the same way, Tang and Liu [16] looked into how ML can be used to identify early labor and fetal distress. They demonstrated that feature selection and ML algorithms might significantly increase results. The papers provide the foundations of applying more sophisticated machine learning models to clinical data, including CTG.

Another significant field of study is the study of physiological markers and autonomic processes that are related to the development of fetuses. Hoyer [17] had an interest in monitoring the progress of a developing fetus and gave attention to indicators of the condition of the autonomic nervous system. Such novel conceptions of assessing body parameters provide a sufficient plausible reason to apply multimodal characteristics in multimodal learning CTG. Karboulut and Ibrikci also proposed to use decision trees and adaptive boosting to determine whether a fetus is in trouble or not [18]. This indicates that ensemble approaches have a potential to enhance individual classifiers to be more dependable and precise. Their work demonstrated the way of enhancing methods to process noisy CTG data.

Neural networks have also played an important role in ensuring that it is easier to predict the health of a fetus. Johnson et al. [19] tested CTG with neural networks and demonstrated that they are able to identify complex patterns that are not noticeable by older statistical procedures. This paper demonstrated that deep learning is able to be trained on large sets of CTG in a dataset-specific manner. This makes way to more advanced architectures. Meanwhile, Homer et al. [20] provided a more clinical perspective of the use of CTG in the fetus monitoring. They underlined the importance and also indicated the issues with false positives and that interpretation may be subjective. Their results render the shift towards machine learning-based automated diagnostic systems even more reasonable.

3. MATERIALS AND METHODS

The proposed system will also entail the construction of an automated fetal health prediction pipeline. It will combine dimensionality reduction techniques (PCA, LDA, KPCA) with advanced classifiers to make CTG-based diagnosis better. First, characteristics borrowed off the UCI CTG dataset will be pruned and made smaller with the help of PCA to eliminate redundancies, LDA to project data to distinguish classes, and KPCA to note nonlinear structure [22]. This will enable the representation of compact and useful ones. Secondly, SMOTE and the additional SMOTEENN sample technique will be resampled to eliminate class imbalance to prevent biased learning. Then, the Logistic Regression, the Random Forest, SVM, the XGBoost, and a Voting ensemble, which includes KNN and XGBoost, will be trained to stabilize the predictions and make them more accurate. Stratified cross-validation and class-wise measures (accuracy, recall, F1, AUC) will be used to evaluate the performance of the model. To demonstrate the contribution of features in making the data easier to comprehend by clinicians, explainable AI techniques like LIME and SHAP will be applied. Real-time input and results display of the CTG will be possible by a lightweight Flask-based user interface. The aim is to produce a fetal health decision-support tool, which is dependable, simple to comprehend, and apply, and has been validated by existing CTG research [25].

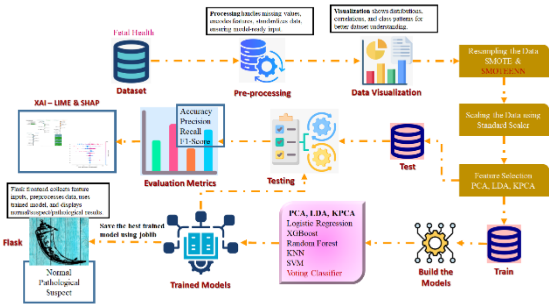


Fig.1 Proposed Architecture

Figure 1 depicts that the ML process of predicting the health of a fetus follows seven steps. Data Collection (1) is the beginning of the process. Preprocessing (2) follows where it involves normalization, standardization, and SMOTE to handle data that is not balanced. Then, Feature Selection is performed with the help of approaches such as PCA and LDA to reduce the number of dimensions (3). The correct methods have been selected in Model Selection (4), such as LR and XGBoost. Training is then done using the model that has been selected. This is a trained program that makes predictions (6) regarding the health of fetuses. Finally, but certainly not the least is Model Evaluations which evaluate the performance of the model (7).

i) Dataset Collection:

The UCI Fetal Health Dataset was used in this study. It contains 2,126 CTG records having 21 features and a target variable that indicates the health condition of the fetus. The characteristics are the fetal heart rate at the time of birth, rate changes, short-term variability and measures correlated with histograms. All these are valuable obstetric monitoring signs. Each instance has three groups, namely, normal (1,655 samples), suspect (295 samples) and pathological (176 samples). This demonstrates that the figures are inherently skewed towards a single category as compared to the other. This lack of balance is similar to the operation in real life medicine where bad outcomes are not as prevalent as usual ones [23]. The dataset provides a full dataset to train machine learning models and dimensionality reduction algorithms that are supposed to make predictions more precise and assist doctors make their decisions.

	baseline value	accelerations	fetal_movement	uterine_contractions	light_decelerations	severe_decelerations	prolongued_decelerations	abnormal_short_term_variability	mean_va
0	120.0	0.000	0.0	0.000	0.000	0.0	0.0	73.0	
1	132.0	0.006	0.0	0.006	0.003	0.0	0.0	17.0	
2	133.0	0.003	0.0	0.008	0.003	0.0	0.0	16.0	
3	134.0	0.003	0.0	0.008	0.003	0.0	0.0	16.0	
4	132.0	0.007	0.0	0.008	0.000	0.0	0.0	16.0	

5 rows × 22 columns

Fig.2 Dataset Collection

ii) Pre-Processing:

Another stage of predicting the health of a fetus is pre-processing. It involves handling missing values, encoding or categorical variables, standardizing numerical features and repairing class mismatch. Right pre-processing ensures that machine learning models receive clean, normalized and useful data in order to make accurate predictions.

a) Data Processing: The raw CTG collection requires a lot of work before it can be used on machine learning. In order to ensure that the data is accurate, missing numbers are located and either replaced or disposed. In case of the existence of categorical variables, they are label-encoded to convert them into numbers which can be included in the modeling. Using z-score normalization to make sure equal scaling and less bias caused by different magnitudes is how numerical features are standardized. The input characteristics are split into the goal variable that displays the health classes of fetus. These measures create a strong, quality data that assists algorithms such as XGBoost, SVM, and KNN to find patterns and relationships quickly that are able to accurately predict the health of a fetus.

b) Data Visualization: The depiction of data assists us in knowing distribution of features and their relations with one another in the CTG dataset. First, there exist count plots where the distribution of results is studied. That demonstrates the imbalance of the classes and prevalence of normal, suspect, and pathological cases. The pair plots and histograms display the distribution of the individual characteristics such as the fetal heart rate at birth, the change in speed, and time. It is through correlation matrices that the features that are multicollinear are discovered and this assists in the techniques of selecting the features as well as reducing the quantity of the features. Such images give you an idea of the dataset and this allows you to make more intelligent preprocessing decisions, identify any potential duplicates and select the most suitable model that will allow you to make more accurate and interpretable predictions about the health of babies.

c) Data Sampling: The mismatch of classes in the CTG dataset may enable most of the classes to easily train the model, thus this may lead to less accurate predictions made by the minority classes such as suspect and pathological cases. This is fixed by using oversampling methods such as SMOTE (Synthetic Minority Over-sampling Technique) and SMOTEENN (a combination of SMOTE and Edited Nearest Neighbors) [24]. SMOTE fakes samples of minority groups by linking existing points and SMOTEENN further refines the data set by removing samples which are too loud. In so doing, we obtain a more balanced dataset where the fair picture of all fetal health classes is reflected. This is because machine learning models are more precise in predicting normal and abnormal outcomes.

d) Feature Selection: The selection of appropriate features reduces the dimensions and removes overfitting, as well as simplifies the model. To carry out this work, we take PCA, LDA, and KPCA in order to extract the most valuable features of the CTG dataset. PCA identifies the linear combinations of the features that capture the most variation whereas LDA aims at the separation of classes by maximizing the ratio of between-class scatter to within-class scatter. KPCA applies PCA to nonlinear spaces and discovers elaborate relationships in data on fetal health. Such dimensionality reduction techniques cause faster work of computers as they eliminate redundant or noise-y features and retain the valuable ones. This allows machine learning models to be more robust in predicting the health of the fetus.

iii) Train & Test:

The data are divided into the training and the testing categories such that the performance of the model can be tested using data that the model has never experienced before. Testing set is used to determine the ability of the model to adapt to new conditions and training set is used to learn patterns and relationships in the features. In order to maintain the original distribution of classes in both subsets, stratified splitting technique is employed to ensure that the minority classes are well represented. This prevents the bias against the majority group and allows the validity of predictions to be put to test in a dependable manner. Before splitting, random mixing is done to get rid of effects caused by ordering and make the model training process more stable.

iv) Algorithms:

Logistic regression is a statistical and machine learning technique that approximates the likelihood of a categorical dependent variable, given some input data. It is applicable to binary as well as multicast classification. It provides values as a logistic and therefore it is easy to interpret and is good at determining the influence of the features. The Logistic Regression classifies CTG data as normal, suspicious or abnormal, and this assists the doctors in determining the impact of various factors on the health of a fetus.

$$P(y = 1 \mid X) = \frac{1}{1 + e^{-(W^T x + b)}} \quad (1)$$

XGBoost is an advanced ensemble learning method, which generates the successive decision trees to reduce the amount of incorrect predictions. It can deal with nonlinear relationships of CTG data, which are complicated and makes classification more credible and reduces overfitting. The results of XGBoost are quite accurate on clinical datasets on predicting fetal health due to its high scalability and stability.

$$\hat{y}_i = \sigma\left(\sum_{k=1}^{K} f_k(x_i)\right), f_k \in F \quad (2)$$

Random Forest creates numerous decision trees and sums up their outcomes to be able to make the system more precise and stable. It takes into account the features of CTG to forecast fetal health, including complicated interactions between factors and minimizing overfitting. This technique is applicable in the process of handling medical data that is very dimensional and is noisy.

$$Gini = 1 - \sum_{i=1}^{C} (Pi)^2 \quad (3)$$

K-Nearest Neighbors (KNN) is a method of predicting the classification of a sample based on the most frequent value of the immediate neighbors. It does not make any assumptions about a particular data distribution and finds local trends. It is applied to categorize the CTG data and predict concerning the health of a fetus. The findings are understandable.

$$distance(x, X_i) = \sqrt{\sum_{j=1}^{d} \left(x_j - X_{i_j}\right)^2} \quad (4)$$

Support Vector Machine (SVM) identifies the optimal hyperplane to separate classes that have the largest distance between them. It is also good with large CTG data and nonlinear associations since it compares estimates with high accuracy with reduced wrong classifications in the assessment of fetal health using kernel functions [21].

$$minimize\ \frac{1}{2}\ ||W||^2 + C\sum_{i=1}^{n} \xi_i \quad (5)$$

Voting Classifier To become more stable and applicable in more cases, Voting Classifier employs more than one model, such as KNN and XGBoost. It also increases the reliability of the system and reduces the chances of mistakes in making decisions in regard to a fetal state being normal, suspicious, or abnormal by integrating various algorithms.

$$\hat{y} = argmax_c\left(\sum_{i=1}^{n} II\ (\hat{y}_i = c)\right) \quad (6)$$

4. RESULTS AND DISCUSSIONS

Accuracy: The ability of a test to distinguish between unhealthy and healthy individuals is referred to as its accuracy. To obtain a conception of the accuracy of a test, we ought to determine the proportion of the cases which is true positives and true negatives. This would be expressed mathematically as.

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} (7)$$

Precision: Precision is the percentage of correctly classified cases or samples in relation to the cases or samples that were correctly classified as positives. Hence, this is the way to calculate the accuracy:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (8)$$

Recall: Recall is a measure used in ML to reveal the ability of a model to locate all the significant cases of a particular category. It indicates the degree of an example of a given classification by a model. Calculation is done by taking a ratio between the number of correctly predicted positives and total number of actual positives.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad (9)$$

F1-Score: F1 score is a method of assessing the accuracy of ML model. It sums up the accuracy and the recall scores of a model. The accuracy measure is the number of times that a model was able to make the correct guess in the entire dataset.

$$F1\ Score = 2 * \frac{Recall\ \mathrm{X}\ Precision}{Recall + Precision} * 100 (10)$$

Table.1 Performance Evaluation – Using SMOTE with PCA

ML Model	Accuracy	Precision	Recall	F1-Score
PCA-Logistic Regression	0.859	0.860	0.859	0.858
PCA-XGBoost	**0.980**	**0.980**	**0.980**	**0.980**
PCA-Random Forest	0.821	0.829	0.821	0.820
PCA-KNN	0.953	0.956	0.953	0.954
PCA-SVM	0.929	0.932	0.929	0.930
PCA-Voting Classifier	**0.980**	**0.980**	**0.980**	**0.980**

Table.1 indicates that predicting fetal health becomes much improved with the use of PCA and SMOTE. XGBoost and Voting Classifier had the best results across all metrics.

Table.2 Performance Evaluation – Using SMOTE with LDA

ML Model	Accuracy	Precision	Recall	F1-Score
LDA-Logistic Regression	0.880	0.880	0.880	0.880
LDA-XGBoost	0.976	0.976	0.976	0.976
LDA-Random Forest	0.821	0.832	0.821	0.818
LDA-KNN	0.966	0.968	0.966	0.966
LDA-SVM	0.936	0.939	0.936	0.936
LDA-Voting Classifier	**0.981**	**0.981**	**0.981**	**0.981**

Table.2 presents the result of classification of fetal health using LDA with SMOTE, Voting Classifier, has the highest accuracy, precision, recall, and F1-Score.

Table.3 Performance Evaluation – Using SMOTE with KPCA

ML Model	Accuracy	Precision	Recall	F1-Score
KPCA-Logistic Regression	0.872	0.872	0.872	0.871
KPCA-XGBoost	**0.966**	**0.966**	**0.966**	**0.966**
KPCA-Random Forest	0.800	0.818	0.800	0.797

KPCA-KNN	0.950	0.951	0.950	0.950
KPCA-SVM	0.912	0.915	0.912	0.912
KPCA-Voting Classifier	0.960	0.960	0.960	0.960

Table.3 indicates that KPCA with SMOTE is easier to use in guessing the health of a fetus and XGBoost and Voting Classifier are the most accurate and reliable.

Table.4 Performance Evaluation – Using SMOTEENN with PCA

ML Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
PCA-Logistic Regression	0.889	0.890	0.889	0.888
PCA-XGBoost	0.982	0.982	0.982	0.982
PCA-Random Forest	0.828	0.855	0.828	0.829
PCA-KNN	0.981	0.981	0.981	0.981
PCA-SVM	0.959	0.960	0.959	0.959
PCA-Voting Classifier	**0.989**	**0.989**	**0.989**	**0.989**

Table.4 indicates that PCA with SMOTEENN is better at predicting the health of the fetus, and Voting Classifier possesses the highest accuracy, precision, recall, and F1-Score.

Table.5 Performance Evaluation – Using SMOTEENN with LDA

ML Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
LDA-Logistic Regression	0.901	0.903	0.901	0.901
LDA-XGBoost	0.982	0.982	0.982	0.982
LDA-Random Forest	0.871	0.888	0.871	0.870
LDA-KNN	**0.989**	**0.989**	**0.989**	**0.989**
LDA-SVM	0.960	0.961	0.960	0.960
LDA-Voting Classifier	0.985	0.985	0.985	0.985

As Table.5 demonstrates, the best overall performance metrics are obtained with the use of LDA with SMOTEENN, though KNN and Voting Classifier have the highest fetal health classification.

Table.6 Performance Evaluation – Using SMOTEENN with KPCA

ML Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**

KPCA-Logistic Regression	0.867	0.869	0.867	0.866
KPCA-XGBoost	**0.981**	**0.981**	**0.981**	**0.981**
KPCA-Random Forest	0.813	0.831	0.813	0.813
KPCA-KNN	0.972	0.973	0.972	0.973
KPCA-SVM	0.915	0.917	0.915	0.915
KPCA-Voting Classifier	0.979	0.979	0.979	0.979

Table.6 indicates that KPCA in combination with SMOTEENN enhances predicting the health of a fetus, and XGBoost and Voting Classifier have the most accurate and consistent results.

Fig.3 Comparison Graph – Using SMOTE with PCA

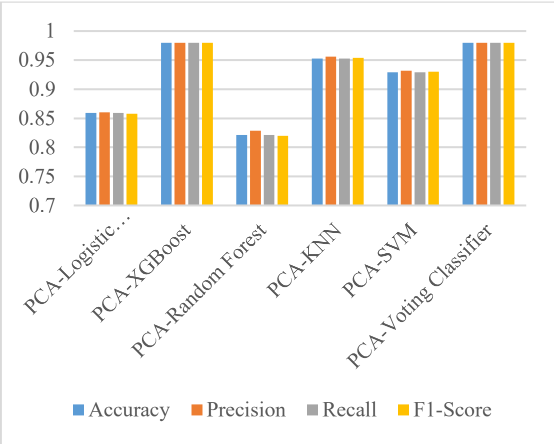
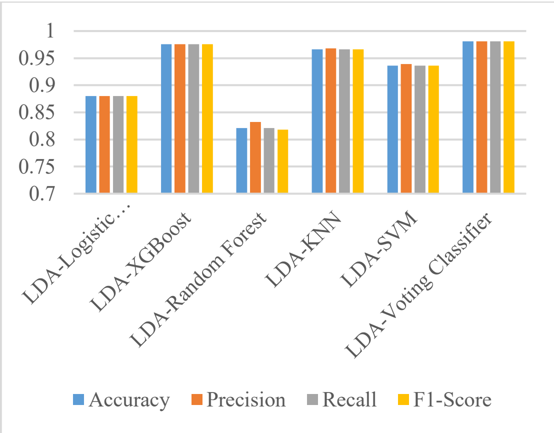


Figure 3 is a bar chart which applies the PCA in order to compare the performance of the various machine learning models.

Fig.4 Comparison Graph – Using SMOTE with LDA



The figure 4 reveals the effectiveness of the model with LDA. It indicates that F1-Score is yellow, Accuracy is blue, Precision is orange and Recall is gray.

Fig.5 Comparison Graph - Using SMOTE with KPCA

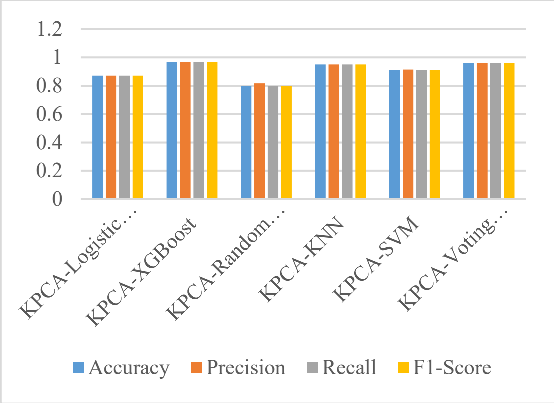


Figure 5 indicates the effectiveness of the model using KPCA and SMOTE. The color of the measurements is the following: Accuracy (blue), Precision (orange), Recall (gray), and F1-Score (yellow).

Fig.6 Comparison Graph – Using SMOTEENN with PCA

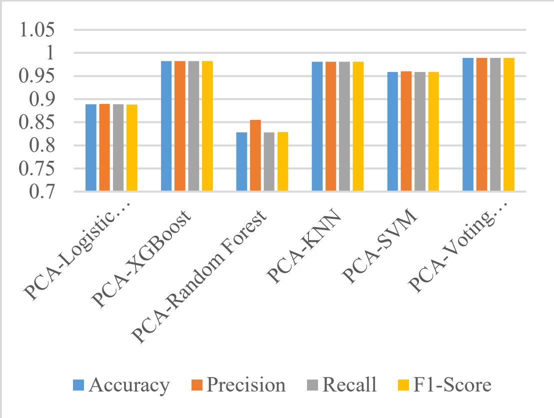
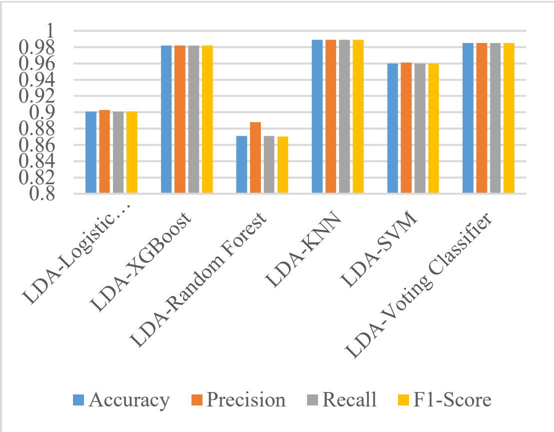


Figure 6 indicates the effectiveness of the model with the use of PCA and SMOTEENN. The measurements are F1-Score (yellow), Accuracy (blue) and Precision (orange).

Fig.7 Comparison Graph – Using SMOTEENN with LDA



The results of the model using LDA and SMOTEENN are shown in figure 7. The measures are indicated by the colors: F1-Score- yellow, Accuracy- blue, Precision- orange, Recall- gray.

Fig.8 Comparison Graph – Using SMOTEENN with KPCA

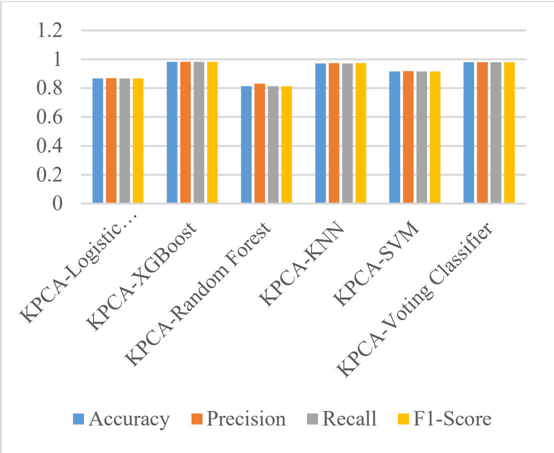


Figure 8 shows the effectiveness of the model when using KPCA and SMOTEENN. The measures are indicated by the colors: F1-Score- yellow, Accuracy- blue, Precision- orange, Recall- gray.

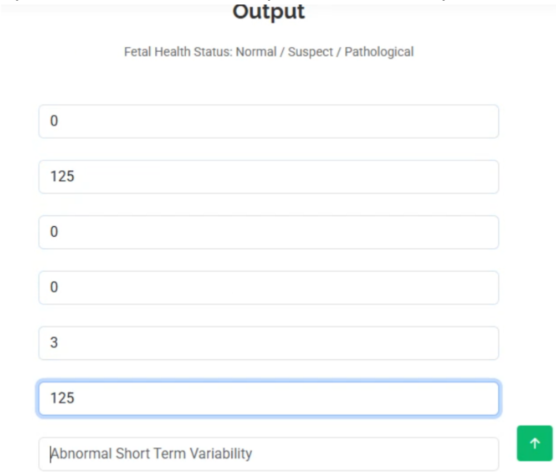


Fig.9 Upload Input Data

Fig. 9: The system takes numbers which are provided by the user to use in making predictions; the system processes these numbers and informs the user of the health state of the fetus.

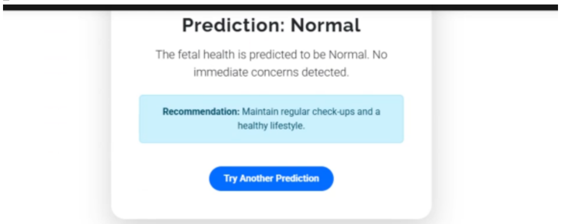


Fig.10 Predict Result

The prediction result, as indicated in figure 10 is that of normal, and a health suggestion.

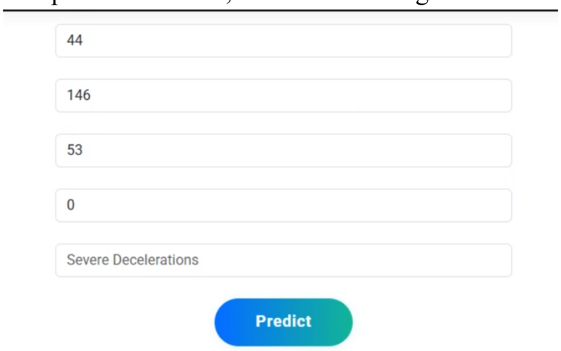


Fig.11 Upload Another Input Data

Figure 11 represents the input port of the system. Individuals are asked to enter figures and then press the button of Predict.

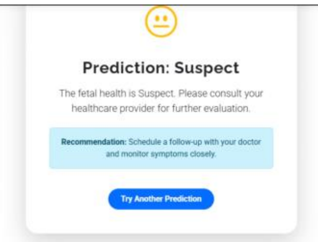


Fig.12 Final Outcome

Figure 12 indicates that the forecast of this system is to suspect and it informs the users that they need to discuss with a doctor to get more information.

5. CONCLUSION

It is demonstrated that with the help of dimensionality reduction techniques applied to CTG data, it becomes significantly easier to make a guess about the health condition that the baby will have. To identify the most effective predictive models, we have tested the PCA, LDA, and KPCA and the more advanced machine learning techniques. The model was also made more robust and applicable in more scenarios by using SMOTE and additional SMOTEENN technique to rectify the imbalance in the classes. PCA-XGBoost and PCA-Voting Classifier achieved 98 percent accuracy with SMOTE, PCA-KNN achieved 96.6 percent, LDA-Voting Classifier achieved 98.1 percent, LDA-KNN achieved 96.6 percent and KPCA-XGBoost achieved 96.6 per cent. This demonstrates that they are not very bad at forecasting the future. The PCA-Voting Classifier obtained 98.9%, the PCA-KNN obtained 98.1%, the LDA-KNN obtained 98.9%, the LDA-Voting Classifier obtained 98.5% and the KPCA-Voting Classifier obtained 97.9% when using SMOTEENN. This demonstrates that ensemble and individual models can be improved with the help of hybrid resampling techniques. These findings indicate that diagnostic accuracy and memory are significantly improved when dimensionality reduction, resampling, and ensemble learning are all used. It also reduces false positives and negatives and ensures that fetal health assessment is not erroneous. In addition, both LIME and SHAP have been implemented to enhance the interpretability to aid in clearing clinical decision-making and a Flask-based interface provided to allow real-time distribution. The findings provide the foundation of high-accuracy automated decision support of clinical fetal monitoring. This will enable prompt action that will enhance the health of a mother and the baby.

Researchers may consider in the future applying more sophisticated deep learning models, such as CNNs and recurrent ones, such as LSTM or BiLSTM, to obtain more accurate information about the health of a fetus. These models have the ability to detect complicated temporal variations in CTG signals. Assembling various types of data such as the medical history of the mother and ultrasound measurements may allow making predictions more precise and allow you to conduct a complete risk assessment. A Bayesian optimization or genetic optimization of hyperparameters can also be used to improve model accuracy and generalization. The inclusion of multicenter CTG records in the data will strengthen the dataset in a broader spectrum of groups. In the clinical cases, it may be easier to observe the fetus throughout the time by use of real-time deployment frameworks and lightweight models of edge devices. This allows the physicians to work promptly and enhances the well being of the baby and the mother.

REFERENCES

[1] Khlystun, O., & Bazilevych, K. (2023). Comparative Analysis of the Machine Learning Dimensionality Reduction Methods on the Example of Fetal Health Determination. In *ProfIT AI* (pp. 140-151).

[2] Choubey, D. K., Kumar, M., Shukla, V., Tripathi, S., & Dhandhania, V. K. (2020). Comparative analysis of classification methods with PCA and LDA for diabetes. *Current diabetes reviews*, *16*(8), 833-850.

[3] Swapna, G., Sreenivasulu, K., Deepika, M., Baseer, K. K., Neerugatti, V., & Viswanath, G. (2025). Brain tumour detection using MRI images in CNN. Advances in Science, Engineering and Technology, 6.

[4] Zannah, T. B., Tonni, S. I., Sheakh, M. A., Tahosin, M. S., Sarower, A. H., & Begum, M. (2025). Comparative performance analysis of ensemble learning methods for fetal health classification. *Informatics in Medicine Unlocked*, 101656.

[5] Nazli, I., Korbeko, E., Dogru, S., Kugu, E., & Sahingoz, O. K. (2025). Early Detection of Fetal Health Conditions Using Machine Learning for Classifying Imbalanced Cardiotocographic Data. *Diagnostics*, *15*(10), 1250.

[6] O. C. Olayemi and O. O. Olasehinde, ''Machine learning prediction of fetal health status from cardiotocography examination in developing healthcare contexts,'' J. Comput. Sci. Res., vol. 6, no. 1, pp. 43–53, Mar. 2024.
[7] N. S. Saragodu, S. N. Hegde, and H. Kaur, ''Prediction of fetal health status using machine learning,'' J. Data Sci., vol. 2024, no. 1, pp. 1–7, Jul. 2024.
[8] Y. Salini, S. N. Mohanty, J. V. N. Ramesh, M. Yang, and M. M.V. Chalapathi, ''Cardiotocography data analysis for fetal health classification using machine learning models,'' IEEE Access, vol. 12, pp. 26005–26022, 2024.
[9] J. V. Y. Chuatak, E. R. C. Comentan, R. L. H. G. Moreno, R. K. C. Billones, R. G. Baldovino, and J. C. V. Puno, ''A decision tree-based classification of fetal health using cardiotocograms,'' Nucleation Atmos. Aerosols, vol. 2562, Jan. 2023, Art. no. 020003, doi: 10.1063/5.0111194.
[10] H. Mukherjee, ''Linear discriminant analysis for fetal health classification in cardiotocographic data,'' J. Healthcare Eng., vol. 2023, pp. 1–11, Jan. 2023, doi: 10.1155/2023/1581273.
[11] G Loge, T Sunil Kumar Reddy, G Swapna, & G Viswanath. (2025). Interpretable AI for Precision Brain Tumor Prognosis: A Transparent Machine Learning Approach. In International Journal of Health Sciences and Pharmacy (IJHSP) (Vol. 9, Number 1, pp. 180–195). Zenodo. https://doi.org/10.5281/zenodo.15523628
[12] A. Singh and J. Sharma, ''Kernel PCA for nonlinear feature extraction in fetal health data,'' Nature Appl. Sci., vol. 2, pp. 151–164, 2021, doi: 10.1007/s42452-021-04391-z.
[13] T. Das, ''Enhanced fetal health classification using kernel PCA and machine learning,'' Int. J. Mach. Learn. Cybern., vol. 12, no. 8, pp. 2153–2164, 2021, doi: 10.1007/s13042-021-01311-w.
[14] T. Nguyen, ''Principal component analysis in feature selection for fetal health classification,'' Diagnostics, vol. 10, no. 5, pp. 1–12, 2021, doi: 10.3390/diagnostics10050238.
[15] M. Chavez, M. Pérez, and C. Ortega, ''Artificial intelligence in fetal monitoring and CTG analysis: A review,'' J. Obstetrics Gynaecol., vol. 39, no. 3, pp. 1–10, 2019.
[16] S. F. Tang and Y. Liu, ''Machine learning applications in predicting preterm labor and fetal distress,'' J. Obstetrics Gynaecol., vol. 37, no. 8, pp. 1035–1041, 2017.
[17] D. Hoyer, ''Monitoring fetal maturation—Objectives, techniques and indices of autonomic function,'' Physiolog. Meas., vol. 38, no. 5, pp. R61 R88, May 2017, doi: 10.1088/1361-6579/aa5fca.
[18] E. M. Karabulut and T. Ibrikci, ''Analysis of cardiotocogram data for fetal distress determination by decision tree based adaptive boosting approach,'' J. Comput. Commun., vol. 2, no. 9, pp. 32–37, 2014, doi: 10.4236/jcc.2014.29005.
[19] B. Johnson, A. Bennett, M. Kwak, and A. Choi, ''Automated evalu ation of fetal cardiotocograms using neural network,'' in Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC), Oct. 2012, pp. 408–413, doi: 10.1109/ICSMC.2012.6377735.
[20] R. Homer, S. Siassakos, A. Crofts, and K. L. Bianchi, ''Cardiotocography and its use in fetal health surveillance,'' Brit. J. Obstetrics Gynaecol., vol. 117, no. 3, pp. 257–264, 2010.
[21] P. J. Johnson and G. Al-Shaikh, ''Cardiotocography in modern obstetrics: Its importance in fetal monitoring,'' Obstetrician Gynaecologist, vol. 3, no. 3, pp. 150–155, 2001.
[22] Salini, Y., Mohanty, S. N., Ramesh, J. V. N., Yang, M., & Chalapathi, M. M. V. (2024). Cardiotocography data analysis for fetal health classification using machine learning models. *IEEE Access*, *12*, 26005-26022.
[23] A D Venkatesh, K Bhaskar, G Swapna, & G Viswanath. (2025). Advanced Hybrid Learning Architecture for Precision Cardiovascular Risk Assessment. In International Journal of Health Sciences and Pharmacy (IJHSP) (Vol. 9, Number 1, pp. 50–61). Zenodo. https://doi.org/10.5281/zenodo.15448632
[24] Almadi, M., Alotaibi, F., Almudawah, R., Ali, A., Nasser, Y., & Nasser, N. (2025, February). Data-Driven Machine Learning Models for Enhanced Fetal Health Classification and Monitoring. In *2025 8th International Conference on Data Science and Machine Learning Applications (CDMA)* (pp. 189-192). IEEE.
[25] Tran, M. H., Rogalski, L. E., & Ahamed, A. (2025, January). Enhancing Fetal Health Diagnosis: A Comprehensive Evaluation of Machine Learning Techniques on Cardiotocogram Data. In *2025 IEEE 15th Annual Computing and Communication Workshop and Conference (CCWC)* (pp. 00599-00604). IEEE.
[26] Amanda, L. R., & Anasanti, M. D. (2024). Assessing Performance Across Various Machine Learning Algorithms with Integrated Feature Selection for Fetal Heart Classification. *International Journal of Artificial Intelligence Research*, *8*(1), 1-14.

[27] Ganesh, B. R., B M, P., Prasad K, K., Swapna, G., & G, Viswanath. (2025). Data Mining-Driven Multi-Feature Selection for Chronic Disease Forecasting. Journal of Neonatal Surgery, 14(5S), 108–124.
[28] Jyostna, G., Goyal, H. R., Soudagar, M. E. M., Parikh, S., Patil, H., & Alaskar, K. (2023, December). Fetal health classification using ai from cardiotocography features. In *2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)* (pp. 1544-1550). IEEE.
[29] Samara, M. N. (2025). A data-driven analysis of maternal health risk indicators using machine learning techniques. *Journal of Medical Artificial Intelligence*, *8*.
[30] Abdullah, A., & Alkadri, S. P. A. (2025). Classification of Fetal Health Using the K-Nearest Neighbor Method and the Relieff Feature Selection Method. *Journal of Artificial Intelligence and Engineering Applications (JAIEA)*, *4*(2), 986-989.