Multi-Stage Dimensionality Learning with Hybrid Classifier for CTG-Based Fetal Health Identification

Bhagya lakshmi Jakkula,
MTech(CSE), Department of CSE,
Eluru College of Engineering and Technology, Eluru,Andhra Pradesh, India - 534004.
bhagyajakkula2805@gmail.com

K.V.Jhansi Rani B.Tech, M.Tech, (Ph.D), Associate Professor
Eluru College of Engineering and Technology, Eluru,Andhra Pradesh, India - 534004.

Dr.Suresh Sundaradasu B.Tech, M.Tech, Ph.D, professor and HOD.
Eluru College of Engineering and Technology, Eluru,Andhra Pradesh, India - 534004.

Abstract—**Accurate assessment of foetal well-being is important to minimise pregnancy problems and provide optimal maternal and newborn outcomes. CTG is a procedure that is often performed to monitor the foetus and provide important information about foetal well being. But manual processing is time consuming and subject to interpretational variation. This study compares the performance of predictive modelling approaches on a UCI Foetal Health Dataset in order to boost the accuracy of a diagnosis using dimensionality reduction approaches like PCA, LDA and KPCA. To address class imbalance, two approaches were used: SMOTE and SMOTEENN. Several ML algorithms such as LR, XGBoost, RF, KNN, SVM and a VC combining KNN and XGBoost were used to assess the performance. PCA-XGBoost achieved 98% accuracy with the help of SMOTE, LDA-Voting Classifier achieved 98.1% accuracy, and KPCA-XGBoost achieved 96.6% accuracy. The PCA-Voting Classifier achieved the accuracy of 98.9% in SMOTEENN, 98.9% in LDA-KNN and 97.9% in KPCA-VC. Moreover, LIME and SHAP enhances the interpretability of models to highlight the most significant contributing features of the CTG, and for transparency in clinical decision making. Also, a Flask-based framework was designed for the real-time foetal health assessment system by implementing the final prediction system. The findings show that the combination of dimensionality reduction and sophisticated resampling, explainable AI and deployable ML can greatly improve the prediction of foetal health and provide a robust, high-precision automated diagnostic help.**

"Keywords—Fetal health, cardiotocography (CTG), dimensionality reduction, PCA, LDA, KPCA, SMOTE, ensemble learning".

I. INTRODUCTION

The diagnosis and timely intervention of pregnancy problems is still one of the major contributors of morbidity and mortality in mothers and fetuses, and remains a major health problem that needs to be accurately diagnosed and acted upon to improve health outcomes. CTG is a very common non-invasive technique for evaluating foetal wellbeing by analysing foetal heart rate patterns and uterine contractions. While very useful for identifying foetal distress, CTG may frequently be misinterpreted because doctors are subjectively different in their interpretation, leading to unnecessary interventions such as cesarean births without an improvement in neonatal outcome [1, 2]. For this reason, the automatic diagnostic methods are increasingly being studied so as to increase the level of accuracy and reduce the possibility of human error in the analysis of CTG [3, 4].

ML has been found useful for a lot of things when it comes to the prediction of foetal health in the context of raw CTG data. In previous studies, ML models were demonstrated to be superior to the traditional diagnostic approaches in the prediction of foetal health problems, particularly when combined with data pre-processing and resampling techniques for addressing the class imbalance issue [5] and [6]. The huge scale and complexity of the CTG data, however, present challenges for the extraction of features and model performance . Dimensionality reduction such as PCA, LDA and KPCA is a powerful tool to reduce the complexity of the dataset without losing the main information [7,8]. Not only do these help to reduce computational effort, they also help in better representation of features that may lead to a better classification of foetal health outcomes.

In recent years, the use of PCA for reducing the redundancy, LDA for improving the class separability and KPCA for recognizing the nonlinear patterns in the medical data have been emphasised [9, 10]. Using the UCI Foetal Health dataset, this paper compared the effectiveness of the PCA, LDA and KPCA in foetal health prediction based on these improvements. The main goal of this work is to construct an automated framework that combines dimensionality reduction and advanced ML models for improving the accuracy of diagnostics, reducing the interpretive variability, and providing reliable decision-support for the obstetric care.

II. RELATED WORK

Since foetal health is an important subject of study because of its immediate impact on maternal and neonatal outcomes, it has been a particular interest of study. Although traditional CTG has been a standard in the clinic for a long time, manual interpretation of CTG is associated with inter-observer variability and low specificity. For this reason, ML and statistical methods have been used to enhance the diagnostic support. Research has begun to focus on dimensionality reduction and classification algorithms to improve accuracy, efficiency and interpretability of foetal health forecasts.

LDA is one of the most explored methodologies which have been used to classify foetal health problems using the CTG data. LDA has the effect of making the classes more separable and provides an easy to interpret model for medical applications. It has been shown to be efficient in identifying patterns of foetal health with high accuracy by Mukherjee

[10]. In the study by Gupta et al. [11] the predictive ability of discriminant approaches was explored and the importance of these approaches for improving neonatal outcome prediction highlighted. LDA is suitable for linear data distribution and fails to work well for nonlinear data distribution that is common in CTG datasets.

KPCA has been more and more used to handle nonlinearity . Non linear characteristics can be extracted from the FH data for improved categorisation as demonstrated by Singh and Sharma [12] and KPCA will be able to do so. Similarly, Das [13] applied KPCA to ML models, and got better foetal health classification by better feature extraction. The studies demonstrate the ability of the KPCA to uncover some latent features in CTG data that were not captured by conventional linear approaches. On the other hand, the PCA is utilised extensively as a dimensionality reduction technique in medical applications. Nguyen [14] used PCA for foetal health assessment. In order to remove noise and redundancy and retain salient features for accurate classification, it is helpful.

In addition to dimensionality reduction, comprehensive reviews have been carried out for artificial intelligence (AI) strategies for CTG analysis. Chavez et al. [15] presented an in-depth analysis of the use of AI in fetal monitoring. They emphasised the potential of DL and hybrid techniques for decreasing human error . Similarly, Tang and Liu [16] explored the potential application of ML to predict preterm labour and foetal distress and showed that the combination of feature selection with ML algorithms can significantly enhance the performance. These reviews are the building blocks for the application of the latest ML models on clinical data-sets such as CTG.

Another major line of research has been searching for physiological indicators and autonomic functions of foetal development. Hoyer [17] has discussed some approaches to monitoring foetal maturation, focusing on indicators of the autonomic nervous system. The observations on physiological data is also important information for the application of multimodal features in ML-based CTG analysis. Ensemble approaches also have been shown to be more resilient and accurate than single classifiers, as done by Karabulut and Ibrikci [18] for foetal distress diagnosis using decision tree-based adaptive boosting. They showed that boosting techniques were a robust way to cope with noisy CTG data.

Improved prediction of foetal health has been made through the use of neural networks. Johnson et al. [19] used neural networks for the evaluation of CTG and demonstrated that the neural networks could recognize complex patterns which could not be recognized by traditional statistical methods. The study demonstrated the adaptability of DL to learn from large amounts of CTG data, which opens up the door to even more sophisticated designs. Meanwhile, Homer et al. [20] provided a more detailed clinical perspective on the use of CTG for foetal surveillance, highlighting the value of CTG and the concern for false positives and manual interpretation. Their observations also help in transitioning towards automatic diagnostic frameworks using ML.

III. Materials And Methods

In the proposed system, the dimensionality reduction method (PCA, LDA, KPCA) will be used to achieve a fully automatic pipeline for foetal health prediction using advanced classifiers with CTG for improved foetal diagnosis. A set of features extracted from the UCI CTG data set will first be denoised, and then be reduced by PCA to eliminate the redundancy features, LDA to separate the classes by projections, and KPCA to capture the nonlinearity features to provide compact and informative data. Then, to achieve unbiased learning, the class imbalance will be addressed by resampling using SMOTE and newly added SMOTEENN method, before which the models LR, RF, SVM, XGBoost and Voting ensemble (KNN + XGBoost) will be trained for the above-mentioned stabilised prediction and accuracy. Stratified cross validation and class-wise measures (precision, recall, F1 and AUC) will be used to test model performance. It will demonstrate the importance of features using explainable AI techniques like LIME and SHAP to give interpretability to the clinicians. A simple user interface using Flask will be created to enable the input and display of results in real-time from the CTG. To develop an interpretable and deployable, well-verified foetal health decision making tool, based on recent CTG studies [25].

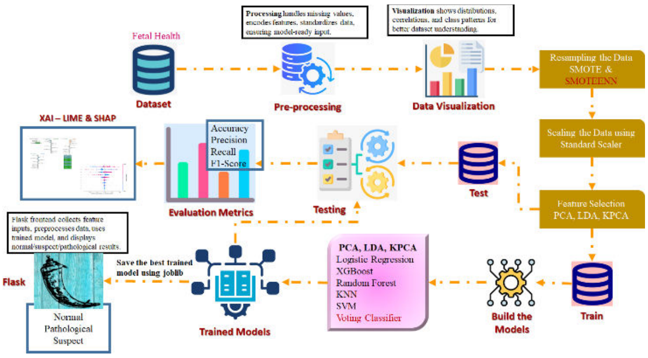

Fig. 1. System Architecture

The prediction of foetal health via ML workflow. The first step is Data Collection (1), the second is Preprocessing (2) comprising of normalisation, standardisation and SMOTE for handling imbalanced data. Then, 3 (Feature Selection) is carried out with the dimensionality reduction method like PCA and LDA. Then, in Model Selection (4), the suitable algorithms are selected. These are Logistic Regression, XGBoost. The chosen model is then utilised for Training (5). The category of foetal health is predicted by a trained model (6). Lastly, Model Evaluations (7) evaluate the performance of the model.

i) Data Set Collection

This research uses the UCI Foetal Health Dataset consisting of 2,126 CTG recordings of 21 characteristics and one target variable indicating the health of the foetus. These elements are: the baseline foetal heart rate, accelerations, decelerations, short term variability and measurements based on the histogram of the foetal heart rate, which are all necessary indicators for obstetric monitoring. The data is divided into 3 classes namely: normal (1,655 samples), questionable (295 samples), and pathological (176 samples) which is evident from the class imbalance problem in data. The imbalance is consistent with the actual medical situation where there are fewer pathological cases than expected given the normal outcome of the case [23]. The data set offers a good cover for evaluation of ML models and dimensionality reduction techniques to enhance the reliability of prediction and clinical decision support.

	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

Pre-processing is an important step in foetal health prediction, which includes missing values management, encoding of categorical variables, standardisation of numeric characteristics and correcting the class imbalance. Clean, normalised and meaningful inputs to the ML models are ensured by the right pre-processing, which allows the models to make the correct prediction.

*a) Data Processing:*The unprocessed data set CTG has to go through multiple data processing steps to be able to feed into the ML process. Data is missing, identified and either imputed or deleted to maintain integrity of data. In case we have any categorical variables, they are label-encoded into a numerical format appropriate for modelling. To avoid biases caused by different magnitudes, numeric features are normalised to a common scale by performing a z-score normalisation. The target variable (foetal_health) is separated from the input features. These methodologies present a homogenous and quality data set, which increases the understanding of the pattern and relationships of the algorithms, including XGBoost, SVM and KNN, and improving the ability for accurate and repeatable learning and prediction of foetal health.

*b) Data Visualization:*Data visualisation helps to understand the feature distributions and relationships of CTG dataset. First, the class imbalance and the appearance of normal, questionable and abnormal instances are explored via count plots. Pair plots and histograms also show the distribution of individual variables, like baseline foetal heart rate, accelerations and decelerations. The correlation matrices are employed to identify the features that are highly correlated with each other, thereby assisting in feature selection and reduction processes. These visualisations give us an overview of the dataset and help us make educated decisions about the data pre-processing, potential data redundancy, and model selection methods to better and more interpretable predict foetal health.

*c) Data Sampling:*Class imbalance in CTG dataset may result in the model being biased towards the majority class and make the prediction performance of the minority classes such as suspect and pathological classes worse. In order to overcome this, oversampling techniques like SMOTE and SMOTEENN are used [24]. The SMOTE generates synthetic instances of minority classes by interpolating between the existing minority instances while the SMOTEENN further cleans the data set by discarding noisy instances. The proposed resampling techniques produce balanced samples, ensuring fair representation within each foetal health class and enhance the reliability, robustness, and generalization of ML models for predicting normal and abnormal outcomes.

*d) Feature Selection:*Feature selection reduces dimensionality of the data, prevents overfitting and improves model interpretability. The three methods of PCA, LDA and KPCA were employed to select the most informative features from the CTG dataset used in this study. PCA is linear combinations of features that maximise variance, whereas LDA is about class separability in maximising the ratio of between-class scatter to within-class scatter. The non-linear extension of PCA is KPCA and is able to learn complex relationships within foetal health data. These dimension reduction methods improve the computational efficiency and also help ML models to achieve higher accuracy in foetal health outcome classification by eliminating irrelevant or noisy features and keeping the essential features.

iii) Train & Test:

The data is divided into training data and testing data to check the performance of the model on unseen data. Training set used to learn the patterns / relationships between features, test set used to test the capacity of the model to generalise to new cases. Preserving class distribution in both halves of the splitting technique yields good representation of minority classes. This avoids a bias towards the majority class and enables for a reliable assessment of the prediction skills. The data is also randomly shuffled before it is divided to reduce any ordering effects and increase the robustness of the model training process.

iv) Algorithms

LR is a statistical and ML technique used for binary and multi class classification. It is a model of probability of a categorical dependent variable based on independent input data. Uses the logistic function to give a value between 0 and 1. This is interpretable and has helped to understand the contribution of features . For foetal health prediction, the normal, suspect and pathological classes are identified by Logistic Regression, where the benefit lies in its ability to uncover the impact of certain features on foetal health.

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

XGBoost is a state-of-the-art ensemble learning technique that builds sequential decision trees to reduce prediction errors. It is effective for modeling non-linear relationships in CTG data, which are sometimes complicated, thereby enhancing the classification accuracy and reducing overfitting. XGBoost is scalable, stable and can be used with clinical data for accurate foetal health prediction [28].

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

The RF algorithm creates a number of decision trees and combines them to get a more accurate and stable prediction. Takes into account complex relationships among variables and minimizes overfitting in the prediction of foetal health by analysing CTG characteristics. This method is applicable to large and noisy medical data.

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

The KNN is a local classifier which assigns the majority class of the sample's nearest neighbours without a distributional assumption. It is applied for CTG signals classification in foetal health prediction and provides intuitive and interpretable results.

SVM is the technique to find an optimum hyper plane which has maximum margin between classes. It can handle high dimensional CTG data and nonlinear interactions effectively by using kernel functions and is able to make good predictions and reduce misclassification of foetal health in assessment [21].

$$minimize\ \frac{1}{2}\ ||W||^2 + C\sum_{i=1}^{n}\xi_i\ (4)$$

VC can be used to combine several models such as KNN and XGBoost, resulting in more stable predictions and better generalisation. It integrates various classifiers and enhances the robustness and reduces misclassification of normal, suspicious and abnormal foetal state.

IV. Experimental Results

*Accuracy:*A test's ability to correctly classify the sick and healthy cases. The accuracy of the test is the proportion of true positive and true negative tests to all tests performed. Mathematically this can be represented as:

$$Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + FP + TN + FN}}\ (5)$$

*Precision:*Precision is the proportion of the relevant instances/samples among the retrieved instances/samples. So the formula of calculating the precision is:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}}\ (6)$$

*Recall:*In ML, it is a metric used to evaluate the performance of a model that measures its ability to identify all the relevant cases of a specific class. It is the ratio of correctly predicted positive observations to the number of the actual positive observations, which gives an indication of the accuracy of the model in predicting positive class observations.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP\ +\ FN}}\ (7)$$

*F1-Score:*F1 score in ML refers to the accuracy of a model. It's a combination of the precision and recall scores of a model. Accuracy: The percentage of accuracy over the entire data set.

$$F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100(8)$$

Table.1 Performance Evaluation – Using SMOTEENN with PCA

ML Model	Accuracy	Precision	Recall	F1-Score
PCA-LR	0.889	0.890	0.889	0.888
PCA-XGB	0.982	0.982	0.982	0.982
PCA-RF	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.1 shows the improvement made in the prediction of foetal health using PCA with SMOTEENN. Voting Classifier has the most accuracy, precision, recall and F1-Score.

Table.2 Performance Evaluation – Using SMOTEENN with LDA

ML Model	Accuracy	Precision	Recall	F1-Score
LDA-LR	0.901	0.903	0.901	0.901
LDA-XGB	0.982	0.982	0.982	0.982
LDA-RF	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

The results in Table.2 show that the LDA with SMOTEENN considerably improves the foetal health classification and the KNN and the Voting Classifier obtained the best overall performance metrics.

Table.3 Performance Evaluation – Using SMOTEENN with KPCA

ML Model	Accuracy	Precision	Recall	F1-Score
KPCA-LR	0.867	0.869	0.867	0.866
KPCA-XGB	0.981	0.981	0.981	0.981
KPCA-RF	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

The KPCA with SMOTEENN enhances the foetal health diagnosis as exhibited in Table.3. Both XGBoost and Voting Classifier provide the best consistent and accurate results.

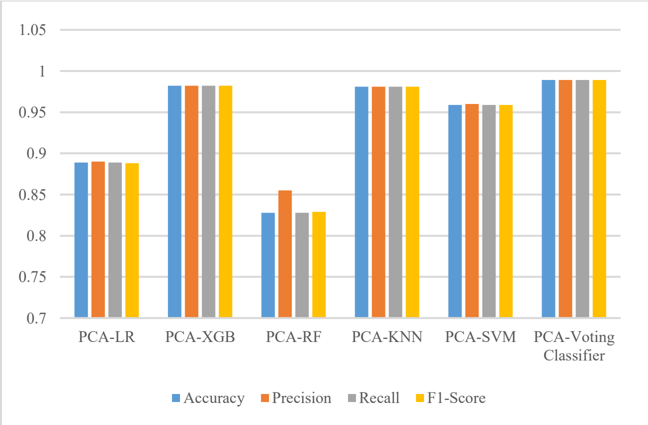

Fig.3 Comparison Graph – Using SMOTEENN with PCA

The PCA based model performance with SMOTEENN is presented in Fig.3. Metrics are: Accuracy, Precision, Recall, F1-Score.

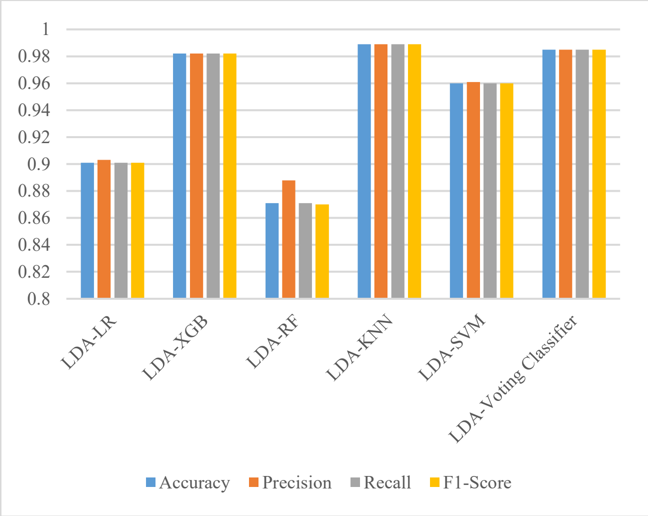

Fig.4 Comparison Graph – Using SMOTEENN with LDA

The performance of the model using the LDA and SMOTEENN is demonstrated in Fig.4. The colours for the measures are : Accuracy (blue) , Precision (orange) , Recall (grey) , and F1-Score (yellow) .

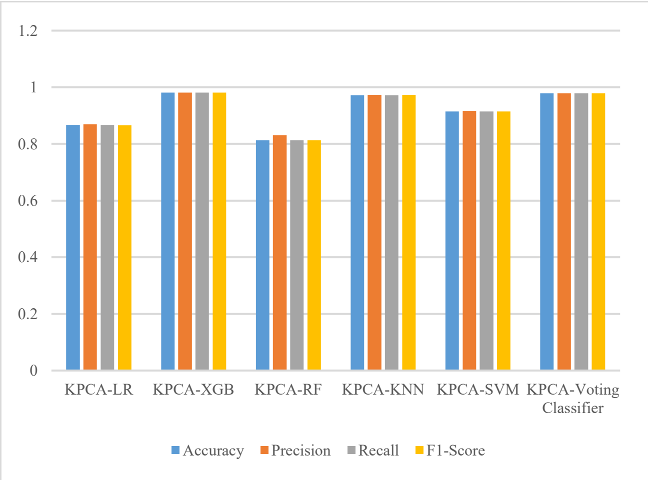

Fig.5 Comparison Graph – Using SMOTEENN with KPCA

Fig.5 shows the performance of the model based on KPCA and SMOTEENN. The colors of the metrics are Accuracy(blue), Precision(orange), Recall(gray) and F1-Score(yellow).

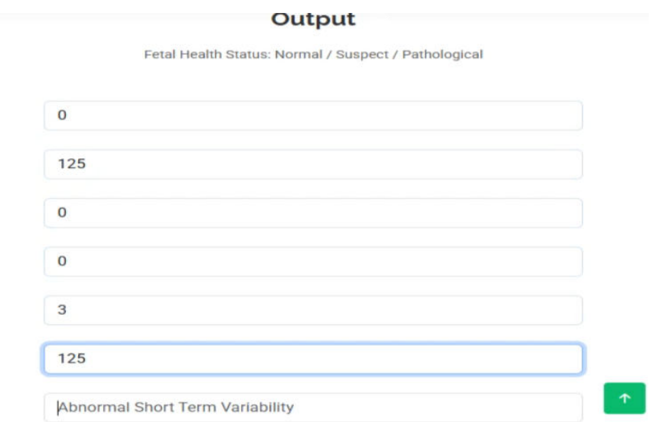

Fig.6 Upload Input Data

Numerical values are entered by user in Fig.6, system processes the values and provides foetal health status.

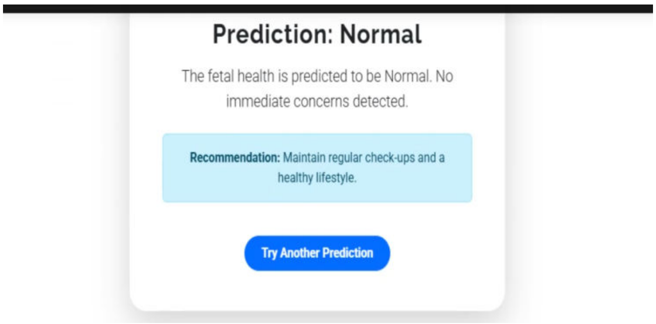

Fig.7 Predict Result

The prediction result is "Normal" and the health suggestion is as shown in Fig.7.

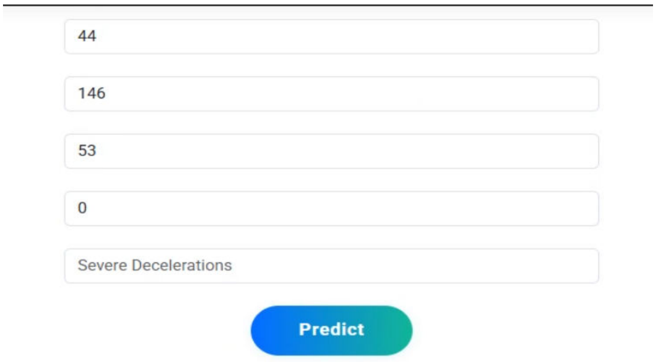

Fig.8 Upload another Input Data

The input interface is shown in Figure 8. The user types in the numbers and then clicks on "Predict".

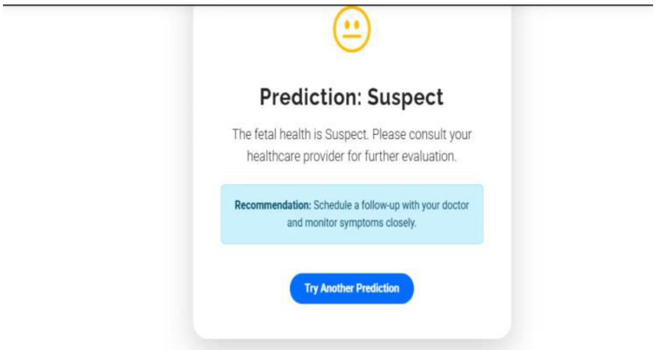

Fig.9 Final Outcome

The system categorizes the system as "Suspect" and recommends for further review by a health care professional in Fig. 12.

V. Conclusion

The study reveals that the use of dimensionality reduction techniques on CTG data greatly enhances the prediction of foetal health. We used a combination of sophisticated ML algorithms and tested integration of PCA, LDA and KPCA to identify the best predicting models. Also, class imbalance problems were solved by SMOTE and SMOTEENN for improving robustness and generalisation of the model. The models PCA-XGBoost and PCA-Voting Classifier achieved an accuracy of 98% while the model

PCA-KNN, LDA-Voting Classifier, LDA-KNN, KPCA-XGBoost had a good predictive performance with an accuracy of 98.1%, 96.6%, 96.6%, and 95.3% respectively. The ensemble and individual model efficacy can be further improved by hybrid resampling techniques. The accuracy of PCA-Voting Classifier, PCA-KNN, LDA-KNN, LDA-Voting Classifier, KPCA-Voting Classifier were 98.9%, 98.1%, 98.9%, 98.5%, and 97.9% respectively on using SMOTEENN. The results show that both dimensionality reduction, resampling and ensemble learning techniques play an important role in the accuracy and recall of the diagnosis, false positive and false negative rates, and reliability of foetal health assessment. Furthermore, we used LIME and SHAP to improve the interpretability by making it easy to make decisions in a transparent clinical manner; we also built a Flask-based interface for practical real-time application. The results provide a strong basis for an accurate automated decision support system in clinical foetal monitoring, facilitating faster interventions and thus improving the outcomes of mothers and newborns.

In future studies, the prediction of foetal health can be improved by using advanced DL models such as CNN and recurrent models like as LSTM or BiLSTM to capture complicated temporal patterns in CTG signals. Having all this data integrated, including mother's clinical history and ultrasound data, could enhance prediction of outcomes and a more comprehensive risk assessment. Further, automated hyperparameter optimisation methods, like Bayesian optimisation or evolutionary algorithms, can be used to optimise the model further for accuracy and generalisation. We will supplement this data set with multiyear CTG recordings to increase the robustness throughout the populations. Real-time deployment frameworks and lightweight models for edge devices enable continuous foetal monitoring in clinical settings, enabling timely interventions and improved maternal and newborn outcomes.

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