An Optimized Support Vector-Based Hybrid Framework for Real-Time Maternal Risk Prediction: GA-Driven Feature Selection and XAI

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***Abstract*—Improving early detection and intervention of maternal health globally is a severe issue which is essential for improving health outcomes. Current maternal risk detection methods fail to provide accurate and interpretable results that clinical staff need to make effective treatment choices. A hybrid framework for maternal risk prediction is presented using Genetic Algorithm for feature selection, fine tuned Support Vector classifier (SVC) and explainable AI in this study. This study uses a dataset from Kurigram, Bangladesh, the framework optimizes feature selection and preprocessing to identify key maternal health indicators. The framework achieved an accuracy of 98.21% and an AUC of 0.9903 with the fine-tuned SVC, a notable result in accurately differentiating between high- and low-risk pregnancies. The framework also provided faster training and testing times, which are ideal for implementation in using real time clinical applications.Transparency in the decision-making process was achieved through the incorporation of explainable artificial intelligence (XAI) methods like LIME, thus allowing the healthcare professionals to interpret the predictions. XAI analysis indicates that prior existence of diabetes is the most influence factor in maternal risk.In addition to these, a web tool was developed to ensure fast and secure predictions of only 0.6-0.8 seconds of latency. This research has yields the findings that AI driven hybrid frameworks can be used to improve maternal health and decision making that will ultimately help to reduce the maternal and infant mortality rate with the early and accurate assessment of health.**

***Index Terms*—Materal risk, Real-time maternal risk, Machine learning, Genetic algorithm, Explainable AI.**

I. Introduction

Prediction of maternal risk is critical to identify pregnancy risks and complications that may result in maternal mortality. Although 34% of global maternal mortality has decreased between 2000 and 2020, women still died from pregnancy-related causes at a rate of more than 287,000 in 2020 [1] [2]. The maternal mortality ratio decreased from 441 to 156 per 100,000 live births in Bangladesh between 2000 and 2022; however, it is higher in the rural areas where health care is less available. In particular, 38% of maternal deaths take place on the day of delivery and illustrate the necessity for immediate risk prediction [3].

While current advancements in maternal health prediction are made, misclassification, lack of interpretability, and the dire need for real time diagnostic tools still exist [4] [5]. Traditional methods have not been able to capture all of the complex patterns in and large datasets and so, they are not able to provide accurate and timely decision making in the poor rural settings where there are a paucity of healthcare resources. Lack of efficient and fast developing interpretable models makes it difficult to act swiftly on the clinical intervention, which is needed to reduce maternal mortality. Healthcare AI is being used more as we began to offer promising solutions to these challenges [6].

In this study, a hybrid approach is proposed that combines Genetic Algorithm based feature selection, optimized SVC, with XAI technique. Moreover, a web application is also developed to allow healthcare professionals as well as individuals in rural areas to use the model in real time. Predictions through the tool are fast and inference latency will be fast, which will improve maternal health outcomes. This study carries the following contributions:

Contributions of This Study:

- GA-driven feature selection optimizes model efficiency by selecting relevant maternal health indicators.
- The tuned SVC model improves classification accuracy, robustness, and generalization.
- XAI techniques like LIME enhance interpretability, aiding healthcare professionals in decision-making.
- Evaluation on real-world data from Kurigram (a remote district from the capital of Bangladesh) to ensure the practical applicability in rural settings.
- A web application is developed to provide reliable, real-time maternal risk assessments.

This study using machine learning with real world data tries to enhance maternal risk detection by supporting health care professionals in decreasing maternal and infant mortality in resource limited settings.

II. Literature Review

This section provides a review of previous studies on maternal risk classification, highlighting key methodologies, findings, and challenges.

MaternalNET-RF represents a deep hybrid model developed from artificial neural networks (ANN) and random forest (RF) to classify maternal health risks in pregnancy according to the paper [7]. The model operated on a dataset that included age and blood pressure information to reach 94.88% accuracy. A drawback of this work stems from its limited dataset size because it could reduce the model's ability to appropriately function with population variety.

Studies show that a Quad Enselble Machine Learning framework (QEML-MHRC) is presented to predict maternal health risks based on real world data, and among the applied model Gradient Boosting Trees model with ensemble stacking showed the best performance in all of the evaluation metrics scoring 0.86 [8], [9]. This findings highlights the possibility of the framework to increase maternal health and speed up the introduction of appropriate intervention.

The research by Al Mashrafi et al. [10] employs machine learning algorithms to analyze maternal risk levels by analyzing 402 nationwide maternal death records from Oman. The Random Forest (RF) algorithm yielded the best results of 75.2% accuracy coupled with 85.7% precision and 73% F1-score after implementing Principal Component Analysis (PCA). Historical data used in the research creates a weakness because the current maternal health patterns and risk elements may not be adequately reflected.

In a recent study, the authors of analyzed maternal health risk prediction through traditional machine learning methods within their research. Decision Tree, LightGBM, CatBoost, Random Forest, Gradient Boosting Machines and KNN served as six classifiers for analyzing a public dataset that consisted of maternal health parameters [5]. Decision Tree demonstrated the most optimal performance by achieving 89.16% accuracy that surpassed other evaluated approaches. The research faces limitations due to its limited sample size together with insufficient description of preprocessing procedures which reduce the overall applicability of obtained findings.

In the article [4], a novel deep learning model, DT-BiLTCN, is proposed to predict maternal health risk as it used a data set of 1,218 samples. Using temporal convolutional network, bidirectional LSTM [11] and decision tree, the model uses support vector machines to achieve 98% accuracy. Important indicators include such as diastolic and systolic blood pressure, heart rate and age of the maternal. The limitations include that of a single dataset, possible overfitting, and complexity of the model may not be applicable to real world clinical use. Findings need to be validated with diversified population.

In the paper [12], several machine learning classification methods are compared for the purpose of assessment of maternal health risk based on a dataset consisting of 1,014 observations. The study employs algorithms such as LDA, QDA, KNN, Decision Tree, Random Forest, Bagging, and Support Vector Machine (SVM). From 10-fold cross validation SVM is obtained as highest accuracy of 86.13%. A potential shortcoming is hyperparameter tuning that might impact model performance and render it hard to pick up optimal parameters.

III. Methodology

A detailed methodology is presented in this section that consists of the approach, techniques and steps involved in the maternal risk classification process.

The overall working procedure for predicting maternal risk is illustrated in the Figure 1.

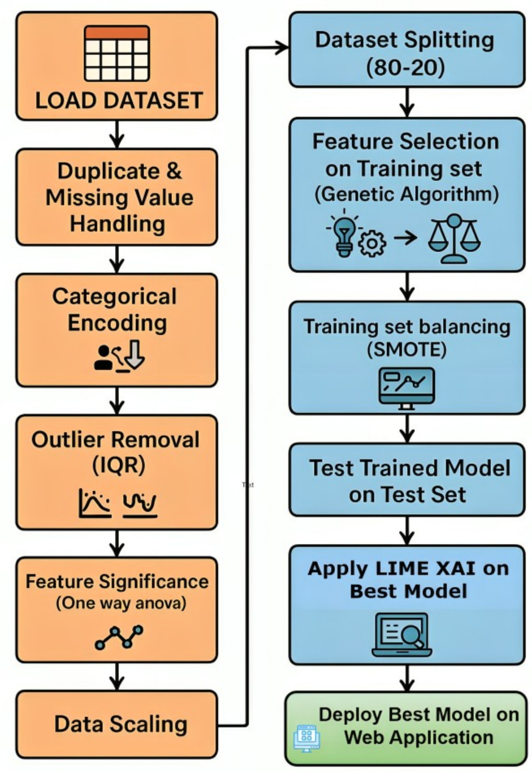

Fig. 1. Workflow Diagram.

A. Data Collection

This study used the maternal risk classification dataset that was obtained from Mendeley data [13]. It has 12 features, including one of which is a categorical and eleven numerical features, and it contains 1,205 observations. Descriptions of features used in this table are provided in Table I.

B. Preprocessing

In order to enhance the level of data quality and reliability, several preprocessing steps were undertaken using the dataset. Duplicate entries were detect and removed to eliminate redundancy. In order to keep data integrity for model training, missing values were handled by removing incomplete entries. To facilitate the machine learning algorithms, categorical variable (Risk Level) was encoded as numerical values. Moreover, outliers were identified and removed with the help of the

TABLE I
FEATURE DESCRIPTIONS OF THE MATERNAL RISK CLASSIFICATION DATASET

Feature Name	Description
Age	Maternal age in years
Systolic BP	Systolic blood pressure (mmHg)
Diastolic	Diastolic blood pressure (mmHg)
BS	Blood sugar level (mg/dL)
Body Temp	Body temperature (°C)
BMI	Body Mass Index
Previous Complications	Number of previous pregnancy complications
Preexisting Diabetes	Presence of preexisting diabetes
Gestational Diabetes	Presence of gestational diabetes
Mental Health	Mental health condition status
Heart Rate	Heart rate (bpm)
Risk Level	Maternal risk classification (High:0, Low:1)

Interquartile Range (IQR) method to combat the influence of extreme values on the model performance. Also, the dataset was standardized as it scales all features to have a mean of 0 and a standard deviation of 1, so that all variables make equal contribution to the model. In these preprocessing steps, a refined dataset lead to improved robustness and accuracy of maternal risk classification.

C. Feature Significance

To discover whether a given set of features are significant in classifying maternal risk, an ANOVA test at 95% confidence was conducted on the data. p values less than 0.05 were taken as relevant features and they were as Systolic BP, Diastolic, BS, BMI, Preexisting Diabetes, Mental Health, and Heart Rate. This includes features for which the p-value is greater than 0.05, further excluded from analysis.

D. Feature Selection

A **Genetic Algorithm (GA)** [14] was used to select features in order to improve feature relevance and decrease computation time. The goal of the algorithm was to determine the best set of features for classification of maternal risk. A **Random Forest classifier** was used to optimize the feature selection process and performance was tracked throughout generations. To facilitate a feature selection process, the settings for the GA are provided in Table II.

TABLE II
GA SETTINGS FOR FEATURE SELECTION

Setting	Value
Population Size	30
Number of Generations	40
Crossover Probability	0.6
Mutation Probability	0.05

E. Feature Importance

Importance of features was evaluated by Bonferroni-corrected test. As can be seen in Figure 2, there is the highest importance for preexisting diabetes, which indicates strong influence on predictions of the model.

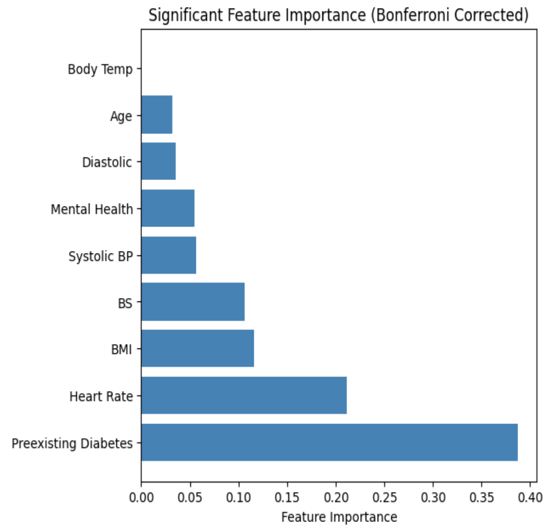

Fig. 2. Feature Importance.

F. Dataset splitting

An 80–20 ratio was used for splitting the dataset into training and testing sets. The shape of the training and testing sets after splitting are added in Table III :

TABLE III
RISK LEVEL DISTRIBUTION IN TRAINING AND TESTING SETS

Set	Risk Level Distribution
Training Set	Risk Level 1: 480, Risk Level 0: 47
Testing Set	Risk Level 1: 121, Risk Level 0: 47

1) Data Balancing: As shown in Table III the Risk Level was shown to be highly imbalanced in the training set. To balance this,resampling is done in both classes to 600 instances using **SMOTE**.

G. Model Training

Performance of the Support Vector Classifier (SVC), Decision Tree (DT), Extra Trees (ET), and Catboost was chosen for interpretability, ability to handle different data types, and performance. In high dimensions, SVC is effective, DT is interpretable, ET reduces oversefitting, and CatBoost handles categorial characteristics efficiently. A Gaussian noise (0.1) was added to all model in the time of training to increase robustness and the hyperparameter was tuned to yield better performance, as tabulated in Table IV.

H. Explainable AI

LIME was applied to the best performing model to improve interpretability of how predictions are made. LIME achieves

TABLE IV
HYPERPARAMETERS FOR EACH MODEL

Model	Hyperparameters
SVC	$C = 2$, Kernel = linear, tol = $1e-4$, max_iter = 1000, probability = True, random_state = 42
CatBoost	iterations = 100, learning_rate = 0.1, depth = 6, l2_leaf_reg = 3, rsm = 0.8, random_seed = 42, verbose = 0
DT	max_depth = 5, min_samples_split = 5, min_samples_leaf = 2, max_features = sqrt, splitter = best, random_state = 42
ET	n_estimators = 100, max_depth = 10, min_samples_split = 5, min_samples_leaf = 2, max_features = sqrt, bootstrap = False, random_state = 42

transparency and reliability in decision making when it highlights the most influential features in maternal risk classification by generating local approximations of the model's behavior.

IV. RESULTS AND DISCUSSION

In this section, we present the results of our analysis on the performance of various models used for maternal risk classification, including both training, validation, and testing outcomes. The performance metrics for the models were evaluated based on accuracy, cross-validation accuracy, training time, testing time, precision, recall, F1-score, AUC, and Kappa score.

A. Training and validation Performance

The training accuracy, cross-validation accuracy and training time for all the models used in this experiment is presented in table V. Both CatBoost and Extra Trees had the highest training accuracy of 98.92% and corresponding 98.52% and 98.62% cross validation accuracy, respectively.Moreover, the other two models also performed well in both training and validation. Support Vector Classifier took 0.1310 seconds and the CatBoost took 0.4557 seconds for training while the Extra Trees took 0.2645 and the Decision Tree model took 0.0095 seconds. These results shows that performance varies among the models, but all of the models have fast training times for real time applications.

TABLE V
TRAINING AND VALIDATION RESULTS.

Model	Accuracy	CV Accuracy	Training Time (s)
SVC	97.25	96.95	0.1310
CatBoost	98.92	98.52	0.4557
DT	97.92	97.65	0.0095
ET	98.92	98.62	0.2645

B. Testing Performance

The testing performance results in Table VI show that the Support Vector Classifier (SVC) achieved the highest accuracy of 98.21% and an AUC of 0.9903, with a testing time of 0.1434 seconds. CatBoost achieved a slightly lower accuracy of 97.62%, but performed better in terms of AUC with a value of 0.9919, taking 0.3536 seconds for testing. The Decision Tree model, while the fastest with a testing time of 0.0493 seconds, had the lowest accuracy of 96.43% and an AUC of 0.9710. Extra Trees, similar to SVC, achieved 98.21% accuracy and an AUC of 0.9882, but required a longer testing time of 0.4228 seconds. Also, the Kappa scores indicated strong agreement between predicted values and actual values for all models with 0.9560 for SVC and Extra Trees and 0.9409 for CatBoost and 0.9125 for Decision Tree. In addition, the Table VII shows the precision, recall, and F1-score for both classes, providing further insight into the models' ability to effectively classify the two categories, which is crucial for evaluating overall testing performance, especially since the testing set is not balanced. This helps in understanding how well the models handle the imbalanced class distribution.

TABLE VI
TESTING PERFORMANCE.

Model	Accuracy	AUC	Testing Time (s)	Kappa
SVC	0.9821	0.9903	0.1434	0.9560
CatBoost	0.9762	0.9919	0.3536	0.9409
DT	0.9643	0.9710	0.0493	0.9125
ET	0.9821	0.9882	0.4228	0.9560

Table VII summarizes the precision, recall and F1 score for each model on the testing set. SVC and Extra Trees achieved the highest precision and recall for both classes, indicating strong classification performance. CatBoost and Decision Tree also performed well, with high precision and recall, particularly for Class 1. Besides these metrics, the confusion matrix and ROC curve added below provide deeper insights into model performance and class separation.

TABLE VII
PRECISION, RECALL, AND F1-SCORE FOR TESTING SET

Model	Class	Precision	Recall	F1-Score
SVC	0	0.9583	0.9787	0.9684
	1	0.9917	0.9835	0.9876
CatBoost	0	0.9574	0.9574	0.9574
	1	0.9835	0.9835	0.9835
Decision Tree	0	0.9184	0.9574	0.9375
	1	0.9832	0.9669	0.9750
Extra Trees	0	0.9583	0.9787	0.9684
	1	0.9917	0.9835	0.9876

According to Figure 3, it is observed that the confusion matrices of Support Vector Classifier (SVC) and the Extra Trees (ET) models are almost the same with 1 false negative and 2 false positives each. On the other hand, the CatBoost model has only 2 false negatives and 2 false positives whereas Decision Tree (DT) model has 2 false negatives and 4 false positives. Overall, SVC and ET models have a lower false negative and false positive in maternal risk classification since they are more reliable in classification.

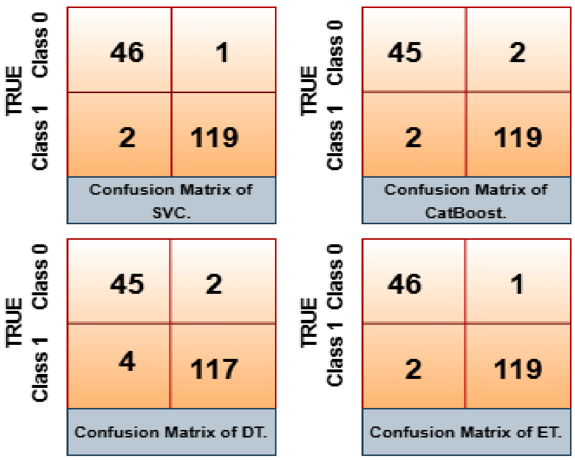

Fig. 3. Confusion matrix of All Model.

All models in Figure 4 demonstrate an exceptional ability for separating the two classes because their ROC curves are near the ideal discriminant boundary. Support Vector Classifier (SVC) demonstrated peak excellence in performance by showing the maximum discrimination ability among all classifiers. The Decision Tree (DT) model presented distortions in its ROC curve because its relatively reduced classification quality among all examined models.

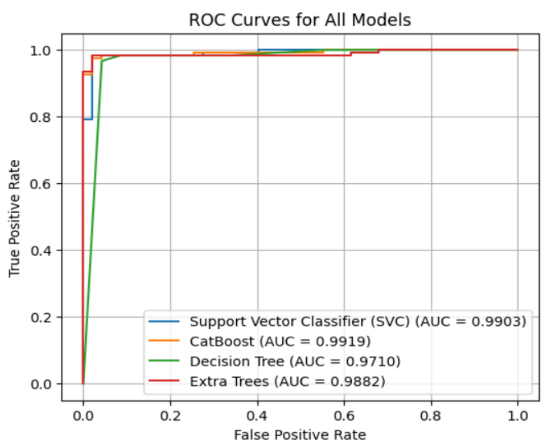

Fig. 4. ROC Curve.

C. Evaluating Model Reliability

The Kappa scores of different models on the test data can be showed in Table VIII. All models demonstrate superior performance according to the Kappa statistic because it evaluates agreement between predicted and actual labels. Support Vector Classifier (SVC) together with Extra Trees achieved the most significant Kappa scores. These scores demonstrate a robust and reliable classification of maternal risk as they show minimal chance-level agreement between actual and predicted labels.

TABLE VIII
MODEL KAPPA SCORE ON TEST SET

	SVC	CatBoost	Dcesion Tree	Extra Tree
Kappa	0.9560	0.9409	0.9125	0.9560

D. Optimized Model for Maternal Risk Prediction.

The Support Vector Classifier (SVC) proved to be the most efficient and best model for maternal risk prediction because it delivered 98.21% accuracy along with an AUC value of 0.9903 and achieved a Kappa score of 0.9560. Additionally, The model also delivered outstanding efficiency as its training process needed only 0.1310 seconds.

Figure 5 incorporates the SVC model's decision boundary which demonstrates its strong ability to properly distinguish the two classes while maintaining low overlapping areas.

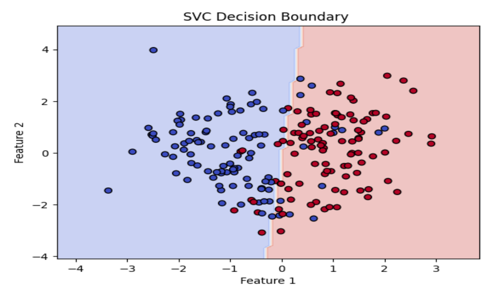

Fig. 5. Decision Boundary of Optimized SVC.

E. Interpretable SVC: Insights from Explainable AI

In Figure 6, the model predicts with 88% probability that the instance is Class 0 (High Risk) and with 12% probability that it is Class 1 (Low Risk). Preexisting diabetes is the most influencial feature for the classification to Class 0 as systolic and diastolic blood pressure have the most impact towards determining the target Class 1. It can be observed from LIME explanation if a person has diabetes, their risk is likely to be high. The model is quite confident where the predicted individual belongs to the high-risk category class 0.

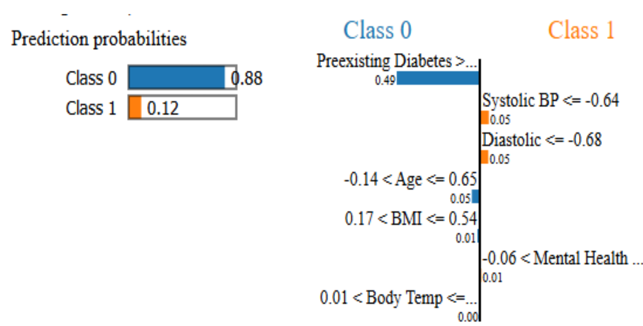

Fig. 6. Interpretability for Class 0.

The model provides 97% probability for the low risk Class 1 outcome and assigns only 0.03% probability to the low risk Class 0 prediction as shown in Figure 7. The main contributors for reaching Class 1 include existing diabetes conditions and patient ages exceeding 0.65 (standardized value) with particular systolic and diastolic blood pressure values. These results indicate that the SVC model confidently classifies the individual as belonging to the low-risk category, Class 1.

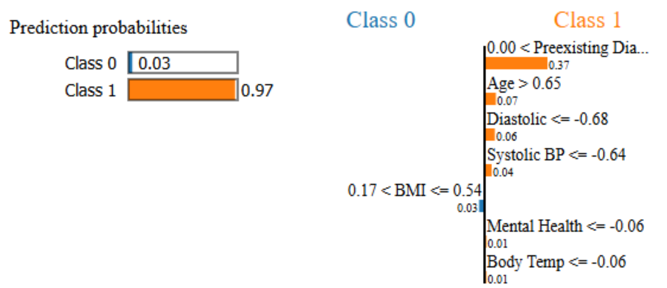

Fig. 7. Interpretability for Class 1.

F. Real Time Detection

A web application has also been developed to detect maternal risk using the optimized SVC model as depicted in Figure 8. It is accessible by individuals as well as by healthcare professionals in rural areas. Results from some of the instances tested on the web app also showed inference latency of 0.6 to 0.8 seconds, which would make it a perfect tool to use on the detection for fast and accurate diagnosis. The web application was built with the aid of Gradio and was deployed successfully to Hugging Face Spaces to perform real-time risk level prediction in accordance with maternal health metrics. In order to guarantee data privacy and security, no personally identifiable information is gathered and stored. In addition, the deployment uses the secure infrastructure of Hugging Face to ensure confidentiality and prevent unauthorized access to the data submitted by users.

G. Comparative Analysis

This study outperforms all the reviewed papers shows in Table IX in terms of accuracy at 98.21% using a optimized SVC. Unlike previous studies, this study employs XAI to make the model transparent and understandable on how it predicts.This enables them to obtain a better understanding and trust of the maternal health risk classification.Also, this study deploy the model in a web application for real time prediction.

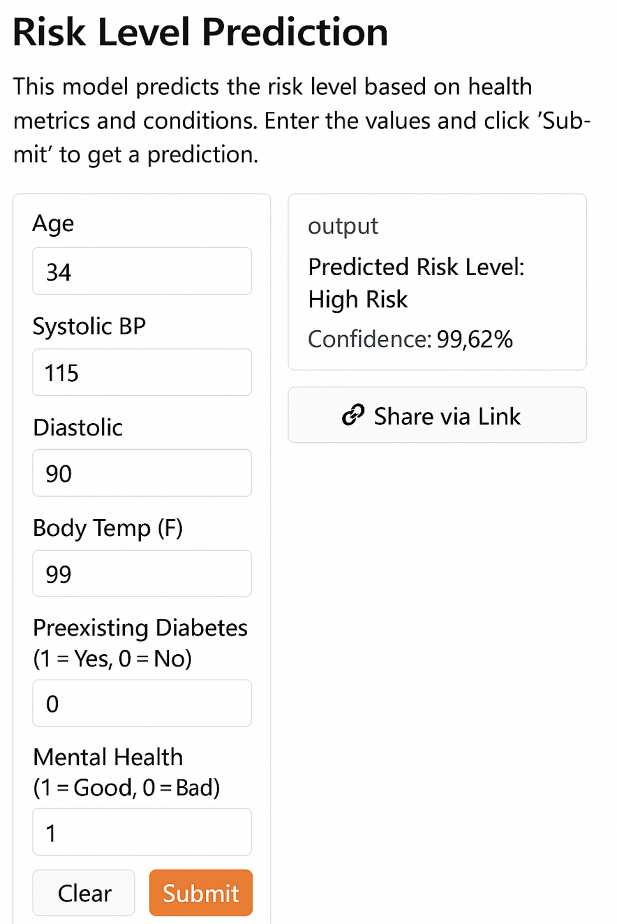

Fig. 8. Web Application for real-time detection of Maternal Risk.

TABLE IX
COMPARISON OF MATERNAL HEALTH RISK CLASSIFICATION MODELS

Study	Best Model	Accuracy (%)	XAI
[7]	Hybrid ANN + RF	94.88	No
[8]	Gradient Boosting Trees (ensemble stacking)	86.00	No
[10]	Random Forest (RF)	75.2	No
[5]	Decision Tree	89.16	No
[4]	Deep Learning (DT, BiLSTM, TCN)	98.00	No
[12]	Support Vector Machine (SVM)	86.13	No
This Study	Tuned SVC	98.21	Yes

V. CONCLUSION

The research develops a hybrid framework to assess maternal health risks by choosing important features with a Genetic Algorithm and optimizing an SVC model while providing clear reasoning for predictions through XAI. The fine tuned SVC demonstrated 98.21% accuracy and 0.9903 AUC to indicate its effectiveness in identifying maternal health risks effectively. Our approach also incorporate XAI methods to show healthcare professionals how the prediction system generates results. The XAI results indicate pre-diabetes poses the biggest danger to women during pregnancy in overall maternal health evaluations. At the same time, a web application tool is developed for real-time detection of maternal risk that is accessible from all parts of the world, including remote areas.

In the future, the model will be continuously trained with larger and more diverse medical records to improve its performance across all patient populations. This system aims to assist healthcare professionals in making informed decisions, ultimately promoting maternal wellness and reducing health issues for both mothers and newborns, particularly in underserved communities.

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