Mom Care: A smart medical app for pregnantwomen

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***Abstract*—Pregnancy is a crucial time in a woman's life, andit needs routine monitoring of both the mother and the fetus. Inthis research project, we propose "Mom Care," a smart medical app that employs machine learning algorithms to predict gestational diabetes, monitors fetal health, and give emotional support to expecting women. Mom Care consists of four major components: the gestational diabetes predictor, the smart chatbot, the fetal health predictor, and the emotion detection utilizing facial expressions and chatbot-based treatment. The gestational diabetic predictor employs machine learning algorithms to predict gestational diabetes risk based on clinical and non-clinical data. The smart chatbot is programmed to give 24/7 care to pregnant women, answering their pregnancy-related questions and offering emotional support. The fetalhealth predictor forecasts the health of the fetus based on CTG data. Lastly, emotion identification based on facial expressions and treatment with a chatbot employs machine learning algorithms to identify and treat emotional discomfort with a smart chatbot. Our experimental findings indicate that the suggested method can accurately diagnose gestational diabetes, monitor fetal health, and give emotional support to pregnant women, hence enhancing their well-being throughout pregnancy.**

Keywords—pregnancy, prenatal care, machine learning

I. INTRODUCTION

Pregnancy is an exciting and demanding period for expectant women. But it may also be a period of uncertainty,particularly in terms of health and wellness management. Many pregnant moms may lack the time or resources to monitor their health during pregnancy due to the hectic pace of modern life. This is a frequent pregnancy condition that can result in a number of health issues. Hence, a dependable and effective system is required to assist pregnant women in managing their health. The objective of our "Mom care: Smart medical app for pregnant women" project is to answer this demand by delivering a comprehensive and individualized approach to maternity care utilizing machine learning techniques.

Recent advancements in machine learning have created new opportunities in healthcare, such as the creation of intelligent medical applications that can assist pregnant women in monitoring their health and well-being. In this research project, we propose "Mom Care," a smart medical app that employs machine learning algorithms to diagnose gestational diabetes, monitors fetal health,24/7 available chatbot and offers emotional support to expecting moms.

Gestational diabetes is a dangerous illness that can have severe effects on both mother and child. The main thing hereis when there is gestational diabetes it can leads to type 2 diabetes in future and there is also a chance that the diabetes occurs during pregnancy may be type 2 diabetes [1]. Our project, "Mom care: Smart medical app for pregnant mothers," intends to assist pregnant women in managing their health by predicting gestational diabetes using machine learning techniques. We used the Pima Indians Diabetes Database from kaggle.com to train and test our machine-learning models to accomplish this goal. KNN, SVM, and RF algorithms were used to predict gestational diabetes in pregnant women. We assessed the accuracy of different methods and chose the most accurate one to incorporate into the final machine-learning model for gestational diabetes prediction. By utilizing this approach, pregnant mothers can proactively manage their health and lower the chance of pregnancy problems. The health of the fetus is a major concern for pregnant moms, andearly detection of any health problems can be crucial for a good pregnancy [2].Using machine learning techniques, our project "Mom care: Smart medical app for pregnant women" intends to give a complete and individualized approach to pregnancy care. We used the Fetal Health Classification Database from Kaggle.com to predict fetal health using machine learning techniques including RF, XGBoost, SVM, and KNN. We assessed the accuracy of these algorithms and chose the best algorithm to incorporate into the final machine- learning model for fetal health prediction. Our initiative intends to assist expectant moms in proactively managing their health and reducing the risk of difficulties during pregnancy by developing a reliable and efficient approach forpredicting fetal health. Our machine-learning algorithms can assist in identifying possible difficulties before they become severe, which is crucial for ensuring a safe and successful pregnancy. Pregnancy can be both an exciting and difficult time, and expectant moms may have numerous questions regarding their health and the health of their growing child. Our project features a chatbot that can answer pregnancy- related inquiries and provide pregnant women with guidance [3]. Using Rasa NLU, we developed natural language understanding models for Sinhala and English chatbots [4].

With the assistance of a doctor who works with expectant women, we manually compiled a dataset to train our chatbot models to comprehend and reply to frequent pregnancy- related questions. The chatbot may not only provide answers to frequently asked queries, but also offer individualized health recommendations depending on the user's current health status. Our project seeks to improve the health and well- being of both the mother and the child by offering an easy and accessible method for pregnant women to gain access to information and assistance. Emotional wellness is an important element of pregnancy and detecting signs of mental stress or depression can be crucial for a good pregnancy. Our project" features a novel feature that employs machine learning algorithms to identify emotions from facial expressions. We developed an emotion identification systemthat can effectively identify emotional states based on facial expressions using CNN algorithms [5]. The technology is connected with a chatbot that leverages Rasa NLU to interactwith pregnant women and deliver individualized assistance. After recognizing the emotion, the chatbot will present a questionnaire to determine whether the pregnant mother is experiencing mental stress or depression. It is vital to diagnose mental health concerns during pregnancy as they can have a substantial influence on the health of both mother and child. Our research aims to promote the health and well-being of pregnant mothers and their infants by providing a holistic approach to emotional well-being during pregnancy.

This research paper on "Mom Care: A Smart Medical App for Pregnant Mothers" provides a novel method for providingindividualized care to pregnant women based on machine learning algorithms. In this study, we present the technique utilized to construct the app, which included the application of KNN, SVM, and RF algorithms to predict gestational diabetes, SVM, Random Forest, XG Boost and KNN to predict fetal health, Rasa NLU for chatbot generation, and CNN algorithms for emotion identification. In Part IV, we give the experimental results and a discussion emphasizing theimportance of our study in enhancing the health and well- being of expecting mothers and infants. Section V concludes the paper, followed by the acknowledgments in Section VI.

II. METHODOLOGY

Predictive analysis requires classification techniques, especially in medicine, where precise predictions might save lives. Machine learning and artificial neural network technologies provide several categorization techniques for this problem. Medical datasets are complicated and imbalanced, making predictive modeling difficult. To address this difficulty, a large dataset is needed to train the model, followed by algorithm development and statistical measurement validation. This research project uses machine learning to create prediction models for diabetes prediction, fetal health prediction, and emotion recognition, as well as aRasa NLU-powered smart chatbot. We aim to construct accurate and trustworthy models to help healthcare practitioners improve patient care.

The processes used to construct a model comprise a number of useful phases that are explained sequentially to illustrate the logic flow underlying this research.

A. Data collection

Diabetes is generally caused by several factors associated with the patients. They can be named as age, gender, disease indications, level of insulin in the blood, high/low blood pressure, and the body-weight [6].The Pima Indians Diabetes Dataset from the Kaggle repository is used for the Diabetic predictor. The dataset consists of 768 records with nine attributes and results. For the fetal health predictor, the Fetal Health Classification dataset is utilized, which contains 2,126 records with 22 characteristics with outcomes. For the creation of the smart chatbot's dataset, the dataset required to be created manually with the assistance of a doctor who works with pregnant women and created for both Sinhala and English languages. Created dataset includes pregnant mothers' frequent questions and answers for them. For Emotion recognizer the data set was created using images of facial expressions obtained from the Internet. Images related to the expressions of anger, happiness, sadness, and tiredness were obtained. About 300 images per pose were included.

B. Data preprocessing

Data preparation approaches play a key role in the development of healthcare machine learning models. The performance of any machine learning algorithm significantly depends upon the organization and distribution of data [7]. Important aspects that impact the accuracy and effectiveness of the model are the quality and quantity of data obtained from pregnant women. The collected data may not be in the proper format and may contain inconsistencies and inaccuracies. Thus, the data must be preprocessed before being fed to machine learning algorithms. Creating an accurate and trustworthy model requires preprocessing techniques such as handling missing values, outlier detection and removal, feature engineering, data encoding, andnormalizing, etc. Using these strategies, we can cleanse and transform the data into a format that can be used for training and testing machine learning algorithms.

1) Diabetic Predictor

Especially when dealing with real-world datasets, data preparation is a crucial stage in machine learning projects. In this study, multiple data preparation approaches were appliedto the Pima Indian dataset to assure the accuracy and reliability of our model for predicting gestational diabetes. We began by identifying and removing all null values from the dataset. Second, we performed outlier detection and removal to mitigate the impact of extreme data on the performance of the model. Finally, we separated the dataset into training and testing sets and balanced it to avoid a class imbalance issue that could result in biased predictions. By performing these preprocessing processes, we sought to provide a clean and well- balanced dataset for our machine-learning model, which could result in more accurate and trustworthy predictions.

finding the null count

```
[ ] df.isnull().sum()

Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

Figure 1 : Finding Null values in Pima Indian dataset.

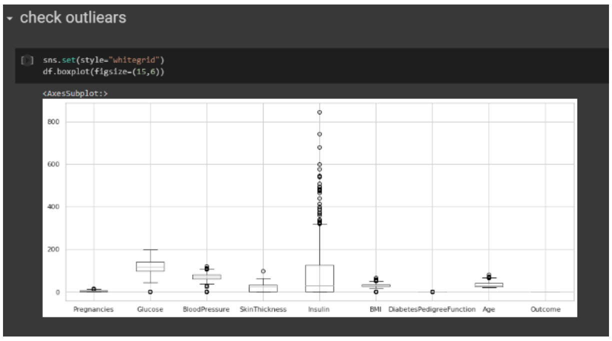

Figure 2 : Find Outliers in Pima Indian dataset.

remove the outliears

```
[ ] Q1=df.quantile(0.25)
    Q3=df.quantile(0.75)
    IQR=Q3-Q1
    #outlier remove
    df_out = df[~((df < (Q1 - 1.5 * IQR)) |(df > (Q3 + 1.5 * IQR))).any(axis=1)]
    df.shape,df_out.shape

    ((768, 9), (639, 9))
```

Figure 3 : Remove Outliers from Pima Indian dataset.

2) Fetal Health Predictor

To ensure the accuracy and reliability of our model for predicting fetal health, various data preparation techniques were used on the CTG dataset. For the fetal health predictor, the first step involved removing duplicate and null values from the dataset to ensure that only relevant data was being used for the analysis. Next, the dataset was split into training and testing sets in a 70:30 ratio. This strategy is frequently employed in machine learning to avoid overfitting, which occurs when the model gets overly complicated and fits the training data too well, leading to a poor generalization of newdata. The dataset was balanced as well to avoid class imbalance problems that can result in biased predictions. Finally, the most associated features were found, which can help to increase the model's accuracy by revealing which features are most strongly correlated with the desired outcome. The goal of the fetal health predictor's data preparation procedures was to provide a clear, balanced, and well-correlated dataset that would increase the precision and dependability of its machine-learning fetal health prediction model.

remove the duplicate values

```
df=df.drop_duplicates()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2113 entries, 0 to 2125
Data columns (total 22 columns):
 #   Column                                                  Non-Null Count  Dtype
---  ------                                                  --------------  -----
 0   baseline value                                          2113 non-null   float64
 1   accelerations                                           2113 non-null   float64
 2   fetal_movement                                          2113 non-null   float64
 3   uterine_contractions                                    2113 non-null   float64
 4   light_decelerations                                     2113 non-null   float64
 5   severe_decelerations                                    2113 non-null   float64
 6   prolongued_decelerations                                2113 non-null   float64
 7   abnormal_short_term_variability                         2113 non-null   float64
 8   mean_value_of_short_term_variability                    2113 non-null   float64
 9   percentage_of_time_with_abnormal_long_term_variability  2113 non-null   float64
 10  mean_value_of_long_term_variability                     2113 non-null   float64
 11  histogram_width                                         2113 non-null   float64
 12  histogram_min                                           2113 non-null   float64
 13  histogram_max                                           2113 non-null   float64
 14  histogram_number_of_peaks                               2113 non-null   float64
 15  histogram_number_of_zeroes                              2113 non-null   float64
 16  histogram_mode                                          2113 non-null   float64
 17  histogram_mean                                          2113 non-null   float64
 18  histogram_median                                        2113 non-null   float64
 19  histogram_variance                                      2113 non-null   float64
 20  histogram_tendency                                      2113 non-null   float64
 21  fetal_health                                            2113 non-null   float64
dtypes: float64(22)
memory usage: 379.7 KB
```

Figure 4 : Remove duplicate values from fetal health classification dataset.

check null count

```
df.isnull().sum()
```

```
baseline value                                            0
accelerations                                             0
fetal_movement                                            0
uterine_contractions                                      0
light_decelerations                                       0
severe_decelerations                                      0
prolongued_decelerations                                  0
abnormal_short_term_variability                           0
mean_value_of_short_term_variability                      0
percentage_of_time_with_abnormal_long_term_variability    0
mean_value_of_long_term_variability                       0
histogram_width                                           0
histogram_min                                             0
histogram_max                                             0
histogram_number_of_peaks                                 0
histogram_number_of_zeroes                                0
histogram_mode                                            0
histogram_mean                                            0
histogram_median                                          0
histogram_variance                                        0
histogram_tendency                                        0
fetal_health                                              0
dtype: int64
```

Figure 5 : Remove null values from fetal health classification dataset.

check if the dataset is imbalance

```
df['fetal_health'].value_counts(normalize=True) * 100
```

```
1.0    77.898722
2.0    13.819214
3.0     8.282063
Name: fetal_health, dtype: float64
```

balance the dataset and divide the dataset

```
X=df.drop(columns=["fetal_health"])
Y=df["fetal_health"]
from imblearn.over_sampling import RandomOverSampler
ros = RandomOverSampler(sampling_strategy="not majority") # String
X_res, y_res = ros.fit_resample(X, Y)
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(X_res,y_res,test_size=0.30)
```

Figure 6 : Balance and divide fetal health classification dataset.

3) Emotion Recognition using facial expressions and Treat using Chatbot

Many data preparation approaches were utilized to prepare our data for training and assessment. Initially, we imported the dataset of facial expression photos using a specialized library and split it 70:30 into training and validation sets. To boost the diversity and quantity of our dataset, we updated the training data using picture changes such as horizontal flipping, rotation, and zooming. The pixel values of the photos were then normalized to the range [0,1] and the labels were transformed to one-hot encoded vectors. This transformation enabled us to express the category labels as a vector of binary values, which our deep learning model can more effectively process. Using the Matplotlib module, we generated an example plot to display the preprocessed photos and their accompanying labels. This graph displays four sample photos from the dataset, along with their associated labels, which are "Anger," "Happiness,""Sadness," and "Tiredness," respectively. The plot enables us to verify that the preprocessing processes have been executed appropriately and that the labels correspond to the face expressions in the photos.

```
[7] class_names = data.class_names
    print(class_names)

    ['Anger', 'Happiness', 'Sadness', 'Tiredness']
```

Figure 7 : Classes for Emotion Recognition

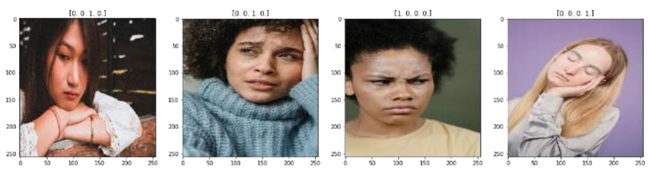

Figure 8 : Four subplots

C. Algorithms used in predictive analysis.

In this study, classification algorithms are employed to construct the final machine learning models for the mom careapp. These classification algorithms are explained one by one.

1) Support Vector Machine (SVM)

SVM is a well-known classification and regression algorithm based on supervised machine learning. The main objective of the SVM is find out the hyperplane in an N dimension space where the hyperplane distinctly classifies the data points [8]. To split the data, it identifies the hyperplane that optimizes the distance between the nearest points of each class. SVM identifies the optimal hyperplane by locating its nearest support vectors or data points. SVM finds the decision boundary that separates data points most effectively while maximizing the distance between support vectors and the hyperplane. This method ensures the extension of models to unobserved data. In several disciplines, SVM may be used for classification andregression.

2) K-Nearest Neighbors Algorithm

KNN is a non-parametric classification approach. A datapoint is classified based on the majority class of its K closest neighbors from the training set. K dictates the performance of an algorithm. Higher K values smooth decision boundaries, but smaller K values make the algorithm more sensitive to data noise. KNN is advantageous when the decision boundary is non-linear or when there are several classes. The processing expense of massive datasets is the key challenge for KNN.

3) Random Forest

Random forest is a popular machine learning ensemble learning method for classification and regression. It's an updated version of the decision tree [8]. Random forest builds multiple decision trees and then merges them all to get more accurate result with stable prediction. It has many decision trees trained on a random subset of features and data points. Combining all tree forecasts yields the final forecast. Pooling weak learners' results prevents overfitting and improves prediction accuracy. It also provides useful information about each feature's prediction value, which may be utilized to choose features and examine results. Random forest is a versatile machine learning method.

4) Gradient Boosting (XGBoost)

To provide the final predictions, Gradient Boosting Machines (GBM) combines the predictions from many decision trees. Every decision tree's nodes each take in a different subset of the data set, giving each tree its own identity and enabling it to identify various signals in the data. While each tree is constructed sequentially for gradient boosting techniques, each tree takes into account the mistakes made by the preceding tree.

5) Bag of World Algorithm

RASA NLU internally uses Bag of Word (BoW) algorithm to find intent and Conditional Random Field (CRF)to find entities.

6) Convolutional Neural Networks

Convolutional Neural Networks (CNNs): are a Deep Learning-based technique [9] that can achieve great recognition precision (Liam Schonevel 2021). CNN consistsof numerous layers, each of which performs a distinct transformation function. CNN has shown to be a useful tool for facial expression-based emotion identification. Our face expression detection job is modeled by a Convolutional Neural Network (CNN). Several convolutional layers, max pooling layers, and fully linked layers comprise the model. The input pictures have a resolution of 256 × 256 pixels and three channels (RGB). The output layer has 4 nodes, one for each facial expression class (happy, sad, angry, and tired), and outputs the probabilities of each class using the SoftMax activation function. This use of CNNs is especially crucial in healthcare, where monitoring maternal mental health throughout pregnancy is essential for ensuring optimal results for both the mother and the growing fetus. CNN-based techniques for emotion identification entail training the network on huge datasets of labeled facial expressions. With a classification layer, the trained CNN learns to extract elements from face photos and map them to certain emotions. This method has the potential to offer expectant moms real- time emotional monitoring, enabling early diagnosis and intervention for individuals at risk of bad outcomes.

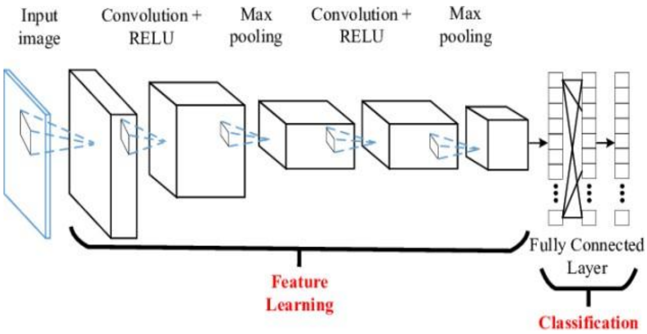

Figure 9: Architecture of the Convolutional Neural Network(CNN)

D. Evaluation Techniques

For the creation of the Mom Care mobile application, the accuracy of the utilized machine learning models was selected as the major evaluative metric. Accuracy is a regularly employed statistic in classification tasks; it indicates the proportion of cases that have been successfully classified out of the total number of occurrences. In the instance of Mom Care, accuracy was especially important because the models were supposed to categorize medical issues and give users individualized health advice. By optimizing for precision, we sought to guarantee that the app's recommendations were trustworthy and beneficial to users. In addition, we explored additional assessment methods like precision, recall, and F1 score, but eventually determined that accuracy was the best applicable statistic forour particular use case.

E. Deployment of Model

Machine learning models have been deployed by developing a Representational State Transfer (REST) Application Programming Interface (API), which accepts input from end users and outputs predictions.

F. Proposed App

We recommend a free Android application titled Mom care, which can be downloaded from the Google Play Store. The app seeks to provide pregnant women with simple access to vital medical information and resources to promote their health and wellbeing. The app has four major components: a gestational diabetes predictor, a smart chatbot, a fetal health predictor, and an emotion recognizer. After downloading the application, users can create a personal account to gain access to these capabilities and receive personalized recommendations based on their own requirements and interests. Using the gestational diabetic predictor, pregnant women can monitor their blood sugar levels and receive alerts and management recommendations for gestational diabetes. The intelligent chatbot offers help and information for typical pregnancy-related inquiries and concerns around the clock. The fetal health predictor uses machine learning algorithms to estimate the fetal health status of expecting mothers based on medical data and give early risk detection. Finally, the emotion recognizer component aids pregnant mothers in monitoring and managing their emotional health. Overall, the mom care Android app offers pregnant moms a practical and comprehensive resource for managing their health and well- being and ensuring a safe pregnancy.

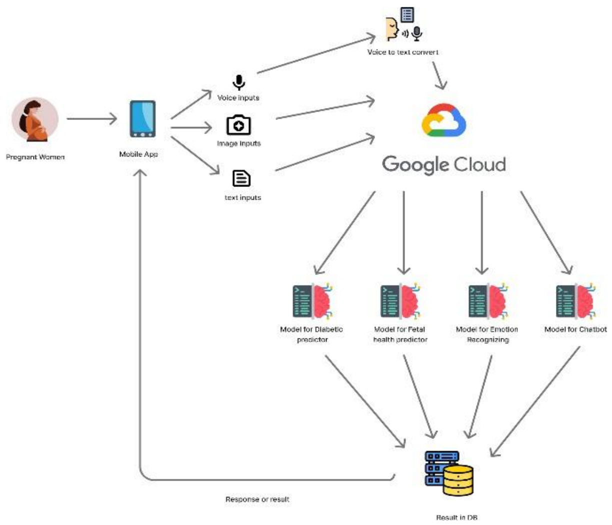

Figure 10 : Overall system diagram for proposed app.

III. RESULTS AND ANALYSIS

Using the Pima Indian Diabetes Dataset, we developed a predictive model for gestational diabetes for this study. The dataset includes medical and demographic data on 768 women, including their age, number of pregnancies, body mass index (BMI), blood pressure, insulin level, diabetes pedigree function, and two outcome variables. The first outcome variable indicates whether the patient developed diabetes within five years of the original examination, whereas the second outcome variable reflects the disease's start. This dataset has been utilized extensively in prior research to forecast the onset of diabetes and test the effectiveness of various machine learning techniques. By evaluating the data and building a predictive model, we were able to determine the primary risk factors for gestational diabetes in pregnant women. Our model can assist healthcare practitioners in identifying women at risk for developing gestational diabetes early in their pregnancies, allowing them to take preventative steps and administer necessary medical care. We did correlation analysis on the Pima Indian Diabetics Dataset to acquire a deeper knowledge of the correlations between the dataset's numerous properties. Our investigation found several intriguing results, including a clear positive link between age and diabetes, with older women having a greater likelihood of developing the disease. In addition, we discovered a positive association between BMI and diabetes, indicating that women with a higher BMI were more likely to get the disease. In addition, we discovered a negative association between insulin concentration and skin thickness, showing that as skin thickness grew, insulin concentration declined. The correlations between numerous parameters can have a considerable impact on the accuracy of predictive models for gestational diabetes. Our gestational diabetes predictor takes into consideration these associations and uses various factors to effectively forecast the risk that pregnant women will develop gestational diabetes. Four machine learning techniques, K-Nearest Neighbors (KNN), Tuned KNN, Support Vector Machines (SVM), and Random Forest, were applied to construct a predictive model for gestational diabetes (RF). The dataset was separated into a training set and a testing set with a 70:30 split, and each algorithm was trained on the training set to predict the likelihood of gestational diabetes in pregnant women based on a variety of medical and demographic characteristics. The KNN algorithm achieved an accuracy of 70.52%, Tuned KNN achieved an accuracy of 82.57%, SVM achieved an accuracy of 78.40%, and RF earned the maximum accuracy of 86.36%, according to our findings. We selected RF as the final machine learning algorithm to predict gestational diabetes in pregnant women based on these results. The high accuracy of the RF algorithm underscores the necessity of employing advanced machine learning techniques to reliably predict gestational diabetes and the possibility for using these approaches in clinical settings to enhance the health outcomes for pregnant women.

```
[ ] df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

Figure 11 : Description of the Pima Indian dataset

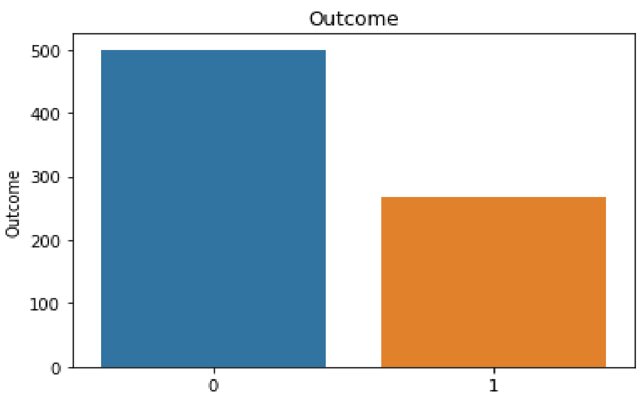

Figure 12 : Outcome of gestational diabetics and non-gestationaldiabetics patients

```
[ ] cor_target = matrice_corr["Outcome"]

    #Selecting highly correlated features
    relevant_features = cor_target.sort_values(ascending=False)

    print(relevant_features)

    Outcome                     1.000000
    Glucose                     0.466581
    BMI                         0.292695
    Age                         0.238356
    Pregnancies                 0.221898
    DiabetesPedigreeFunction    0.173844
    Insulin                     0.130548
    SkinThickness               0.074752
    BloodPressure               0.065068
    Name: Outcome, dtype: float64
```

Figure 13 : Correlations between attributes in Dataset

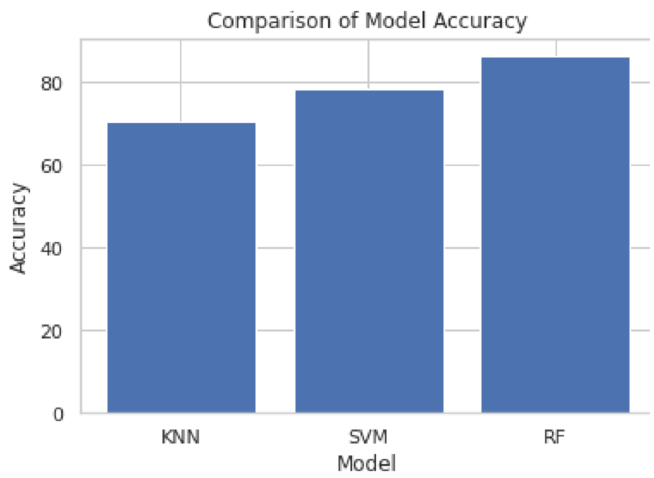

Figure 14 : Accuracy comparison for gestational diabetic prediction

```
[ ] loaded_model = joblib.load('model.joblib')
    def customPredict(data_fields):
      dfToCheck = pd.DataFrame(data_fields, index=[0])
      return loaded_model.predict_proba(dfToCheck)[:, 1][0]

    dict_to_pre = {"Pregnancies":0,
                   "Glucose":0,
                   "BloodPressure":0,
                   "SkinThickness":0,
                   "Insulin":0,
                   "BMI":0,
                   "DiabetesPedigreeFunction":0,
                   "Age":0

                   }
    print(customPredict(dict_to_pre))
```

Figure 15 : Final model for diabetic predictor

The Fetal Health Classification dataset contains information on fetal health markers such as fetal heart rate, uterine contractions, and fetal movements. The dataset includes 2126 properties, including 21 fetal Cardiotocography (CTG) features, 10 non-invasive cardiotocography (NCT) features, and one fetal state label representing the fetus' health status. The CTG characteristics include information on the fetal heart rate, variability, and accelerations, whereas the NCT characteristics include information on the mother's age, weight, and gestational age, among other aspects. Dependingon the health status of the fetus, the fetal state is labeled as Normal, Suspicious, or Pathological [10].This dataset is a significant resource for training machine learning algorithms to predict fetal health status and deliver individualized advice to expectant moms to facilitate a successful pregnancy. During the data preprocessing phase of our fetal health prediction for Mom care research project, we took several steps to assure the quality of the data utilized for training and testing our machine learning models. Then, we detected and eliminated any duplicate values from the dataset to prevent training bias. Finally, we examined the null count to validate the completeness of the dataset, as missing data could compromise the correctness of the model. We also examined if the dataset had a disproportionate number of Normal casesin comparison to Suspicious and Pathological cases. To address this disparity, we utilized data balancing approachesto build a more equal dataset, hence enhancing the predicted accuracy of our models. Lastly, we divided the dataset into training and testing sets using a 70:30 ratio, with 70% of thedataset used to train the predictive model and the remaining 30% used to evaluate the model's accuracy. These data preprocessing methods were critical in maintaining the reliability and accuracy of our machine learning models for predicting the fetal health status of pregnant women. To develop the most accurate machine learning model for predicting the fetal health status of pregnant mothers using the Fetal Health Classification dataset, we compared the performance of several well-known algorithms, includingRandom Forest (RF), Support Vector Machines (SVM), K- Nearest Neighbors (KNN), tuned KNN, and XGBoost. After training and evaluating our models with various algorithms, we discovered that Random Forest had the best accuracy at 99.25%, followed by Tunned KNN at 98.17% and XGBoostat 96.44%. 84.54% was the lowest accuracy for SVM. Due to its excellent accuracy and robustness against overfitting, Random Forest was selected as the optimal technique for developing our final machine learning model for predicting fetal health status. Overall, our results illustrate the efficacy of machine learning algorithms for forecasting the fetal healthstatus of pregnant moms and highlight the need of selecting the most accurate algorithm for predictive modeling. The precision, recall, and F1 scores for the prediction models are shown in Table I. As shown in the table Random Forest exhibits the best performance, achieving a 0.98 F1 score. With respect to the accuracy of the positive predictions, Random Forest achieved a 0.98 precision, and it also achieved a 0.98 recall score which contained a high percentage of total relevant results that were accurately classified. Figures 1 and 2 illustrate, respectively, the confusion matrix and classification report that was produced regarding the predictions for fetal health.

Algorithm	Precision	Recall	F1 Score
RF	0.98	0.98	0.98
SVM	0.84	0.84	0.84
KNN	0.97	0.97	0.97
XGBoost	0.98	0.98	0.98

Table 1

Algorithm	Accuracy
Random Forest	98.38%
XGBoost	96.42%
SVM	85.96
KNN	97.77

Table 2

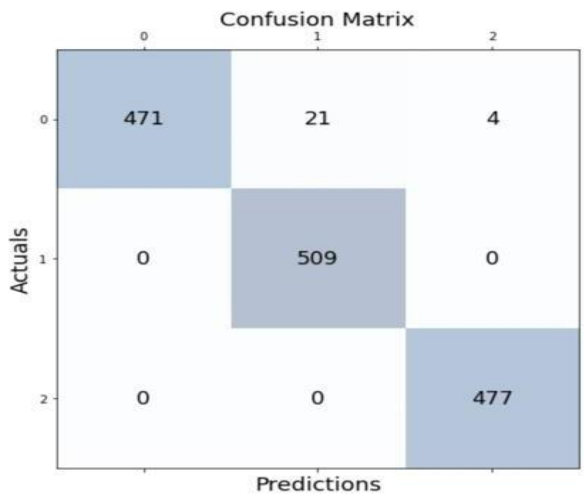

Figure 16 : Confusion Matrix

	precision	recall	f1-score	support
1.0	1.00	0.95	0.97	496
2.0	0.96	1.00	0.98	509
3.0	0.99	1.00	1.00	477
accuracy			0.98	1482
macro avg	0.98	0.98	0.98	1482
weighted avg	0.98	0.98	0.98	1482

Figure 17 : Classification Report

The testing process for emotion recognizing executes to ensure the objective of this application is achieved. The accuracy is determined on emotion based on facial expression image that has been entered into an application through the mobile phone camera. To conclude the overall accuracy performance, the average accuracy is calculated. Below shows the formula for accuracy calculation. Accuracy = (Number of correct prediction /Total number of all cases) * 100% During the training phase of our deep learning model for facial expression recognition, we used the fit() function to train the model over 10 epochs. We obtained a final training accuracy of 93.15% and a validation accuracy of 79.02%, with a corresponding training loss of 0.1747 and a validation loss of 0.6697. These results suggest that our model is learning to classify facial expressions accurately, and is generalizing well to new, unseen data. After the model is trained, the accuracy and loss curves for both the training and validation sets are plotted using the history object returned by the fit () function. The history object contains the training and validation accuracy and loss values for each epoch.

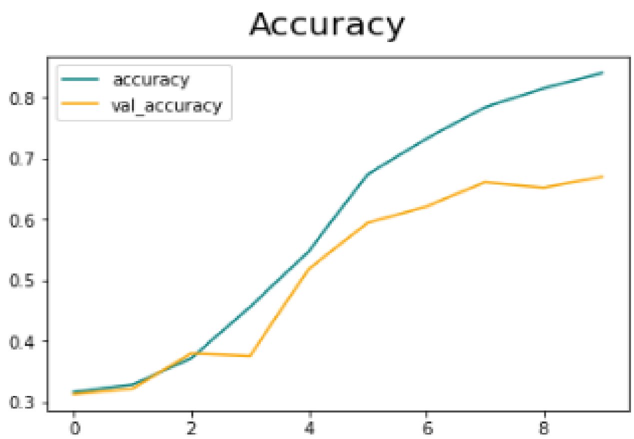

Figure 18 : Accuracy

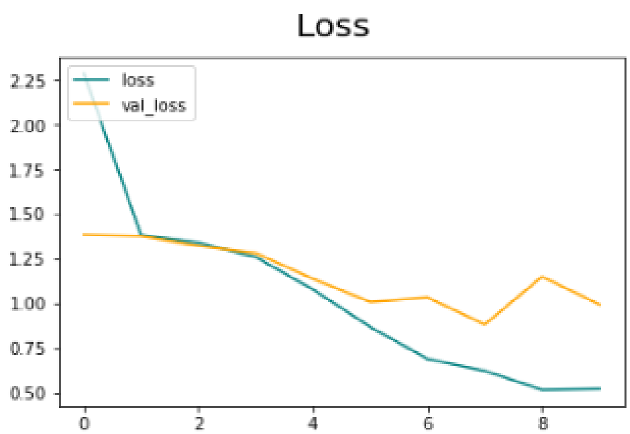

Figure 19 : Loss

IV. CONCLUSION

The "Mom care: Smart medical app for pregnant women" program offers a novel approach to adapting prenatal therapy to the specific needs of each mother. The use of machine learning algorithms has enabled accurate forecasts of gestational diabetes and fetal health as well as the understanding of emotions based on facial expressions possible. Due to the chatbot function, expectant mothers can obtain information on pregnancy, pose questions, and receive responses without leaving their homes. This project's performance in predicting gestational diabetes and fetal health and in identifying mental stress and unhappiness demonstrates that machine learning algorithms have considerable potential in obstetrics and gynecology. This program has the potential to change the healthcare system by providing a low-cost, easily accessible, and individualized solution to improve the health of pregnant women and their infants.

V. FUTURE WORK

Future work for this research project includes incorporating additional features such as nutrition tracking or exercise monitoring, conducting user feedback and usability testing, collaborating with medical professionals to ensure alignment with best practices in prenatal care, and considering internationalization efforts to increase the app's reach and impact on global maternal health.

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