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Application of multi-layer deep learning network for prediction of maternal health

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Abstract: In contemporary research, Artificial Intelligence (AI) and Machine Learning (ML) are vital for predicting pregnancy-related issues by analyzing extensive datasets to create synthetic patterns for personalized assessments. This study focuses on maternal health during pregnancy utilizing a deep learning model, particularly a type of ML that employs multi-layered Artificial Neural Networks (ANN) to discern patterns in data. Two robust linear sequential models based on dense networks were developed using Python, tested with datasets from open-source repositories. The models utilized fifteen variables, including fourteen inputs and one output, with birth weight as the outcome variable. The foundational model consists of five dense layers, while the advanced model includes two additional layers, totaling seven. Model performance was assessed through precision, accuracy, F1-score, and recall rate, with data split into 80% for training and 20% for testing. The basic model trained over 100 epochs with a batch size of 16 recorded an F1-score of 86.22%. In contrast, the advanced Dense CNN linear Sequential Maternal-Health (DCNN-SMH) model achieved a higher F1-score of 91.34% and an accuracy rate of 95% for both prediction and classification, outperforming the base model, which had an accuracy of 93%. The study concludes that advanced dense network models yield superior accuracy compared to base neural networks.
Keywords: *Dense neural network, Linear sequential model and maternal health, Multi-layer network, Sequential layers.*

1. Introduction

Globally, maternal morbidity and mortality have become a matter of great concern. Predicting pregnancy-related risks is considered necessary for addressing issues early and for increasing the well-being of both the mother and the unborn child. Preterm birth, gestational diabetes, and hypertension are some pregnancy conditions that demand close monitoring, as they can have major impacts if left unnoticed. Infants with low or high birth weight are likely to increase morbidity and mortality rates. In this context, deep learning is a potential technique to directly predict unborn babies' weight. A deep belief network (DBN), one of the deep learning methods, has been used to predict fetal weight based on different ultrasound parameters. The results of Al Mashrafi, et al. [1] demonstrate that the proposed deep learning model can be considered a reliable tool for natal weight at fetal age between 15-40 weeks. Of late, the application of deep learning for pregnancy-related prediction has developed. The findings of analysis exhibited that Random Foresting is one of the best-performing algorithms for analyzing maternal risk level, with an increased accuracy level of 75.2%, followed by KNN [2].

Deep learning has been employed in the medical field for various activities, particularly drug discovery, maintaining e-medical records, and medical imaging analysis. Deep learning algorithms contribute to making diagnosis easier by finding intricate relationships, aiming to reduce medical errors, and increasing the population's well-being. The proposed model in the study [3, 4] demonstrated that it

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can assist medical experts in making more accurate birthweight predictions by using routinely gathered antenatal parameters, thereby facilitating appropriate medical decisions and treatments.

Machine learning and deep learning are being used by medical field experts to improve their decision-making in the context of treatment priorities and specific maternal health indicators [2]. These techniques make it possible for healthcare experts to identify and control risk factors in advance by facilitating early risk detection in prenatal care. Consequently, an interesting method to improve pregnancy risk screening is to incorporate machine learning models into healthcare systems [5]. As deep learning approaches deliver all the high-dimensional time series, ranging from low-level to higher-dimensional medical information, it can be definitely employed for potential risk prediction throughout pregnancy. It is also possible with deep learning to address some of the challenges in medical data [6] and extensively contributes to boost such models to surpass human diagnostic capabilities [7]. The findings of Venkatasubramanian [8] emphasized that the integration of deep learning for continuous monitoring of maternal health features exhibits the potential resources of these techniques in ensuring stability and accuracy level [9] when considerable medical dataset is recorded.

Machine learning techniques can address nonlinear issues, which largely take place in human physiology as a result of complex connections between social drivers of health, medical and biological components. The techniques do this by finding out rules and patterns in data to develop prediction models. The accuracy of machine learning models in predicting and analysing unfavourable pregnancy results before they take place has been examined by Sufriyana, et al. [10]. For example, sophisticated and intricate techniques, which could handle both organized and unstructured medical data, including diagnosis results, for example deep learning-based or hybrid models, largely deliver high prediction accuracy [11]. Machine learning and deep learning techniques are highly recommended for predicting medically relevant events, enhancing clinicians' awareness of high-risk cases, and supporting improved clinical decision-making processes. The findings of Vasudevan, et al. [12] emphasize a huge need to increase efforts to translate, execute, and assess the use of the machine learning models in medical practice.

In general, pregnancy and childbirth mortality rates are increased by various factors, including time, distance, and the lack of physicians and nurses [13, 14]. Machine learning algorithms are being widely used to predict a pregnant woman's risk factors and a newborn's condition to track and estimate their risk levels. The algorithms used in deep learning are trained to search through large datasets for patterns and characteristics, enabling them to reach conclusions and make predictions based on newly available data. The Gaussian Naive Bayes, XGBoost, Random Forest, SVM, and Decision Tree (DT) are five major machine learning algorithms that play an important role in predicting maternal health and the weight of newborn babies [15]. These algorithms together can generate the best and most effective outcomes.

1.1. Problem Statement

In the present day, reducing the maternal mortality ratio (MMR) has become an important objective in the global sustainable development goals (SDGs). To reduce mortality and morbidity, decision-makers and healthcare professionals are working hard to predict and identify high-risk groups throughout pregnancy. Pregnancy risk prediction techniques, which are scalable to real-time applications and understandable across populations, are considerably lacking from the existing literature, despite the fact that machine learning and deep learning have shown promise in maternal health prediction and fetal weight prediction. The need for an effective technique which combines various deep learning algorithms to improve accuracy and increase transparency was not adequately addressed by existing studies. Thus, the study is specifically carried out to analyze the role of deep learning in predicting maternal health, particularly birth weight of the baby and health of the fetus. Low birth weight can possibly lead to severe negative consequences on the mother's health, such as neonatal mortality and a number of health concerns throughout their life. To address this problem, this research has been conducted using deep learning to uncover significant factors affecting birth weight and to identify the best predictive deep learning model. The study develops and tests deep learning models for predicting complications related to maternal morbidity and mortality effects.

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2. Literature Review

In Sharma, et al. [13] proposed a solution using machine learning to enhance the accuracy and prediction of birth weight and assist clinicians in recognizing major risks prior to birth. Regression models, including support vector machine, artificial neural network, elastic net regressor, logistic regression, k-nearest neighbors, ridge regressor, random forest, and lasso regressor, are adopted for predicting fetal birth weight based on gender, maternal age, gestational weeks, and ultrasound measurements such as femur length, abdominal circumference, and biparietal diameter. The most influential parameter in predicting fetal birth weight is abdominal circumference, while gender is the least influential. The elastic net regressor model was the best predictor for fetal weight at birth across 15 to 40 weeks of gestation.

Gao, et al. [16] developed a machine learning model for predicting birth weight during the third trimester of pregnancy, which could help minimize adverse fetal and maternal outcomes. In this research, neonatal delivery and maternal results, along with parental demographics, sonographic fetal biometry, and obstetric clinical data, were retrieved from electronic medical records. Machine learning algorithms such as multi-layer perceptron, extreme gradient boosting, random forest, support vector machine, and ridge regression were used to develop the prediction model. The proposed model showed the best performance for macrosomic fetuses and low birth weight infants.

In Henry [17], it was mentioned that infants are measured by maternal experiences during pregnancy. These include the physical health of pregnant women, prior pregnancy experiences, social-environmental health indicators, and emotion regulation. This research models machine learning for predicting markers of fetal development and growth, newborn head circumference, and birth weight. Head circumference was best forecasted with ridge regression (linear model). Infant gender, maternal body mass index, and number of kids predicted high head circumference, while maternal preeclampsia, ethnicity or race, and previous preterm history predicted smaller head circumference. Birth weight was forecasted with support vector machine. It was observed that occupational prestige forecasted higher newborn weight; ethnicity or maternal race forecasted lower newborn weight; challenges with emotional clarity, number of kids, and previous preterm history had nonlinear impacts.

In Alabbad, et al. [18], research was conducted to improve infants' birth weight prediction using machine learning algorithms. Two datasets were analyzed with various algorithms, including AdaBoost, Light Gradient Boosting, Extremely Randomized Trees, and Decision Trees. Results indicated that the Extra Trees model achieved a 98 percent prediction accuracy on the King Fahd University Hospital dataset, while the Random Forest model reached 96 percent accuracy on the IEEE dataset. The study suggested that machine learning systems could provide consistent and reliable predictions.

In Keerthana and Suvanam [19] predicts newborn weight using models in machine learning. Various regression models using support vector machine, linear, ensemble (extreme gradient boosting + gradient boosting) models, ElasticNet, extreme gradient boosting, and ridge were analyzed. It was observed that the ensemble model had a high prediction rate of 90 percent with accuracy, whereas other models like ridge, extreme gradient boosting, ElasticNet, linear, and support vector machine achieved less than 80 percent accuracy in prediction. The ElasticNet model achieved 34 percent accuracy, extreme gradient boosting 77.7 percent, support vector machine 42.9 percent, and linear models 39 percent. The findings indicate that ensemble models, such as combining extreme gradient boosting and gradient boosting, showed better performance with higher accuracy.

In Ranjbar, et al. [20] developed a model for machine learning to predict low birth weight. Predictive models were developed using various algorithms, including permutation feature importance with k-NN (k-nearest neighbors), support vector machine, decision tree classifier, light gradient boosting, deep learning feedforward, random forest classifier, extreme gradient boosting, and logistic regression. Extreme gradient boosting was the best machine learning model for predicting low birth weight, with a recall of 0.69, accuracy of 0.79, F1 score of 0.77, and precision of 0.87. Ranking the features revealed that gestational age and previous low birth weight history were the main predictors.

In Mursil, et al. [21] introduced a new technique using deep neural network for predicting neonatal birthweight with the history in early gestation. Newborn weight is the main predictor of neonatal health, with low newborn weight increasing risks of mortality and morbidity. The role of ultrasonography to monitor fetal health, its restrictions in accessibility and accuracy, needs more effective predictive systems. This research adopts both the TabNet model and a deep learning model. The TabNet model shows the best capabilities in prediction, achieving an accuracy of 96 percent and an AUC of 0.96. Folate status and maternal vitamin B12 are the main predictors of birth weight, representing key nutritional factors impacting neonatal health issues. It was observed that combining multimodal maternal factors offers significant advantages in predicting neonatal birth weight.

Factors that affect fetal and maternal health during early to mid-pregnancy could impact fetal development. This research developed a machine learning model by incorporating artificial intelligence. Various machine learning classifiers were deployed. In this research, stacked ensemble models such as Anchor, LIME (local interpretable model-agnostic explanations), and SHAP (Shapley additive explanations) were developed. When estimating the machine learning classifiers, the AdaBoost model obtained high performance with a maximum F1 score of 72 percent, accuracy of 77 percent, recall of 77 percent, and precision of 73 percent. Furthermore, it was noted that the stacked model showed an accuracy of 75 percent, indicating its potential in clinical applications. The developed model identified some main attributes influencing newborn weight, such as parity, maternal height, crown-rump length, hypertensive disorders during gestation, glycated hemoglobin, nuchal translucency thickness, and plasma protein during pregnancy [22, 23].

In Reza and Salma [24] carried investigation using data to identify the main aspects of low newborn weight using different approaches in machine learning and for determining the best predictive machine learning model and feature selection technique. Logistic regressions were used as a conventional method, along with a few classifiers in machine learning, including naïve Bayes, adaptive boosting, decision tree, random forest, extreme gradient boosting, and support vector machine, to determine the best model for predicting low newborn weight. It was found that machine learning methods perform better than conventional methods, with RF (random forest) being the best model for predicting low newborn weight.

3. Materials and Methods

The architecture of the deep learning (DL) model for predicting maternal health has been described in the following section.

3.1. Proposed Design

The design and flow diagram of the research are represented in Figure 1.

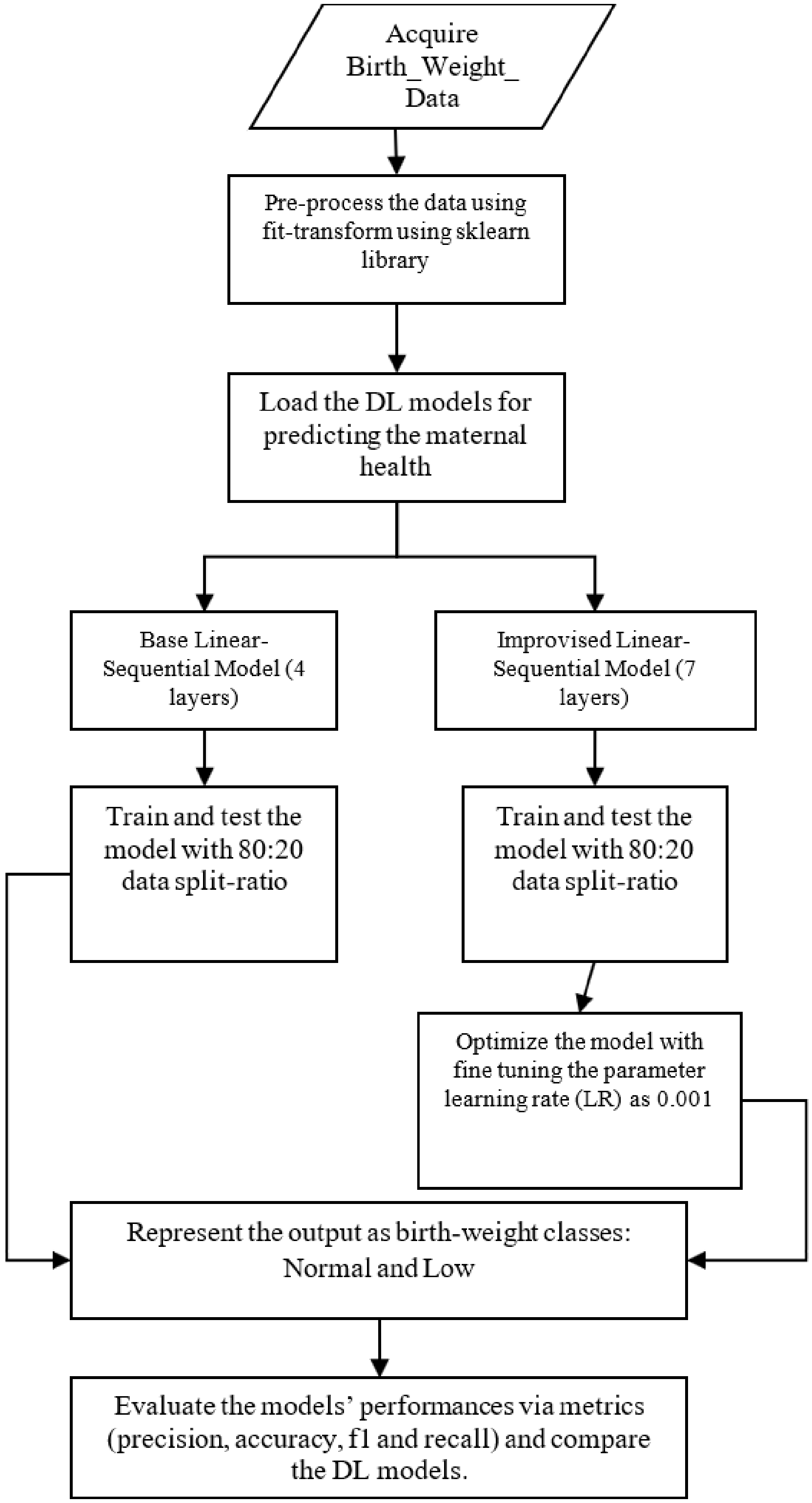

Figure 1.
Research design-flow.

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Based on the research flow, it is apparent that the deep learning model developed here uses sequential linear layers.

3.2. Proposed Architecture

The research adopts a sequential deep learning (DL) model with four layers. The first layer is a linear layer with a kernel size of 1x14 for input and 1x64 for output. It is followed by a ReLU activation layer and a dropout layer, each with kernel sizes of 1x64 for input and output. The fourth and final layer is a linear layer with 1x64 input and 1x2 output. Building on this base model, the research developed an improved linear-sequential DL model with seven layers, adding three layers to the original. The additional layers include a ReLU layer as the fifth layer with a kernel size of 1x32, a dropout layer as the sixth with the same kernel size, and a linear layer as the seventh with a kernel size of 1x32 for input and 1x2 for output. The architecture of the proposed DL model, as shown in figure 3.2, comprises a total of seven sequential layers.

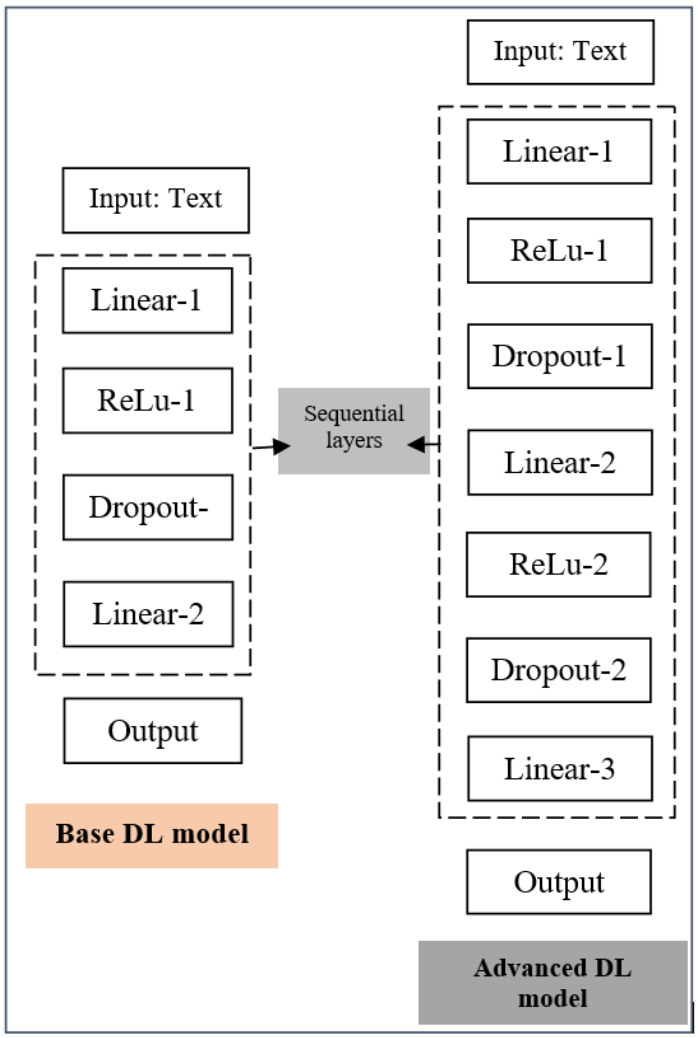

Figure 2.
Proposed DL models' linear-sequential architecture layers.

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The above figure 2 shows the differences in the sequential layers of the base model and advanced improvised DL model. Major reasons behind fine-tuning machine learning models' performances are: improving performance, data efficiency, accessibility, personalization, and providing leverage in knowledge via transfer learning. The current research focuses on fine-tuning the parameter learning rate to increase the model's performance.

3.3. Dataset

This section explains how the data are acquired, cleansed, and balanced. Similarly, the parameters, targeted respondents, and samples used are also briefly explained.

3.3.1. Parameter

The data acquired here is obtained from Kaggle, collected in Ziya [25], with the fifteen parameters as the main variables. They are illustrated in Table 1.

Table 1.
Parameters used and data type.

S. No	Feature	Description	Data type
1.	Age	Mother's age (in years)	Integer
2.	Pre_pregnancy_bmi	Body-Mass-Index of the mother pre-pregnancy	Integer
3.	Gestational_age_weeks	Gestational-age of fetus at birth (in weeks)	Integer
4.	Blood_pressure_systolic	Systolic blood-pressure (in mmHg)	Integer
5.	Blood_pressure_diastolic	Diastolic blood-pressure (in mmHg)	Integer
6.	Hemoglobin_level	Concentration level of the Haemoglobin (in g/dL)	Integer
7.	Number_of_prenatal_visits	Total prenatal visits to the healthcare	Integer
8.	Has_diabetes	Mother's diabetes information (0=No and 1 = Yes)	Integer
9.	Has_hypertension	Mother's hypertension information (0=No and 1 = Yes)	Integer
10.	Smoking_status	Mother's smoking habit while pregnancy information (0=No and 1 = Yes)	Integer
11.	Alcohol_consumption	Mother's alcohol habit while pregnancy information (0=No and 1 = Yes)	Integer
12.	Education_level	Mother's educational level (None, Primary, Secondary and Higher)	String
13.	Household_income	Monthly income (in local currency)	Integer
14.	Iron_supplementation	Mother's iron supplementary information (0=No and 1 = Yes)	Integer
15.	Birth_weight_category	Target variable: Normal and Low, classification	String

3.3.2. Target and Sample

The sample adopted here is the entire dataset, that is 200 samples (i.e., n=200).

3.3.3. Data Split

The training and testing ratio (data split) adopted is 80:20; where the testing is split into 10 for validation and the other 10 for testing.

3.3.4. Model Improvisation

The improvised model's learning rate is set at 0.001 with a random state of 42. Initially, the training of the model is carried out with 100 epochs; after improvisation, the epoch runs are increased to 300 for better performance. Overfitting and underfitting issues are addressed with the early stopping technique.

3.3.5. Inclusion and Exclusion Criteria

Here, focus on the "pregnant" for inclusion and "not pregnant" as exclusion data, respectively. Based on the acquired results, the outputs are classified into pre-defined respective classes (Normal: 1 and Low: 0) to predict birth discrepancies via maternal health.

4. Implementation and Results

This section delves into the tools used, methods adopted, and how the prediction models in detail, along with the results from the models developed (base and improvised).

4.1. Implementation

The models developed to predict maternal health of respondents are created using the Python environment as the application. The software and hardware requirements for the models adopted here are as follows (refer to Table 2).

Table 2.
Requirements of the machine learning models developed.

Hardware:	
CPU	Intel i7
GPU	NVIDIA GPU – RTX 3060 (12 GB)
RAM	16 GB
Storage	SSD with 1 TB capacity
Network speed	1 Gbps
Software:	
OS	Linux - Ubuntu
Language	Python version 3.5
Frameworks	Pandas, numpy, torch, keras in tensor flow and sklearn (Scikit-Learn) and matplotlib

The deep learning (DL) models (base and improvised) developed use dense CNN (dense convolutional neural networking) based linear-sequential layers. The base, as explained, has four layers, whereas the improvised has seven layers for better performance. The developed advanced dense CNN linear-sequential model (refer to Figure 3) focuses on improving prediction and classification accuracy more than the base model.

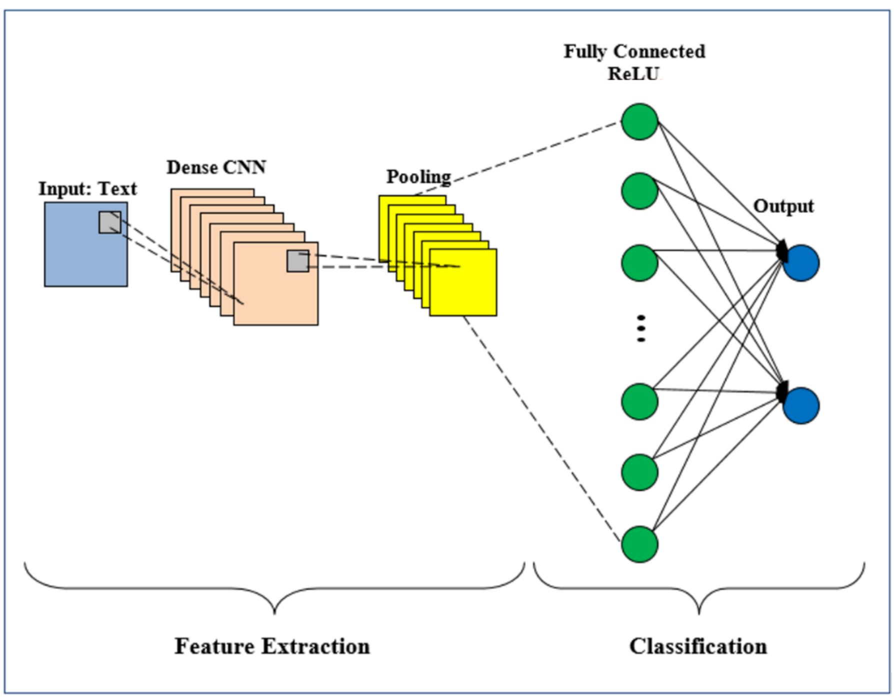

Figure 3.
Dense CNN Linear-Sequential Maternal-Health prediction model (DCNN-SMH model).

The developed model obtains the input (numeric value) in textual (alpha-numeric) form and not as images in this research. Hence, by adopting the linear sequential layers, the analysis is carried out in the dense CNN architecture. Once the data area is examined via the feature extraction method, they are passed through pooling layers to reduce spatial dimensions and then later passed to ReLU function layers for classification purposes. The final outcome is the result/output, which is categorized into pre-defined classes "Normal" and "Low" under maternal health, respectively. Once the models are executed, the performances are compared via accuracy, loss, and F1 scores of both models to identify the best model. The loss, accuracy, and F1 scores are obtained for the base model with 100 epoch runs, and for the advanced DCNN-SMH model, the same metrics are evaluated using 300 epoch runs. Simultaneously, by fine-tuning the learning rate parameter, the DCNN-SMH model is trained to stop early for better performance, to avoid overfitting issues, and to acquire the best accuracy from training and validation.

Thus, the pseudo-code for the dense CNN with linear-sequential layers-based networking models used here is represented as:

Pseudo-code: Dense neural network Algorithm

Step 1: Initiate;

Step 2: Load the datasets acquired for maternal healthcare prediction in Python with fifteen parameters (14 input and one output: Target);

Step 3: Pre-process the data by transforming string values to numeric values. Split the data into 80:20 for training and testing;

Step 4: Define the neural network models (Dense and Fully Connected: ReLU function) with drop out layer;

Step 5: Compile the models with Optimizer (Adam optimization), Metrics (precision, recall, accuracy and f1-score), and Loss (categorical cross-entropy);

Step 6: Training: Define epochs, random state, batch size and the parameter to adjust (i.e., learning rate (lr) for fine-tuning), and lastly validate the epochs on testing datasets;

Step 7: Evaluation: Using test data, predict the outcomes, convert them into class labels (Normal and Low);

Step 8: Compare the actual and predicted labels to generate classification reports (f1-score, recall, accuracy and precision);

Step 9: Produce graphs and confusion matrices for the loss, accuracy and pre-defined classes.

4.2. Results and Discussions

The results of the models are represented as graphs (loss and accuracy) and confusion matrices for each DL model, respectively. Lastly, the comparison of the models and performance metrics of the models are also represented as a bar diagram, individually.

4.2.1. Base Model

As mentioned earlier, the training and validation of the base model are carried out with 100 epoch runs, where the random state is set at 42 with batch size of 16. The class imbalance issue here has been handled by not generating any synthetic data. Thus, the 100 values (loss, accuracy, and F1-scores) are obtained for the base model. Few sample values from the actual data gained are depicted in Table 3.

Table 3.
Epoch values for base model.

Epochs	Train_Loss	Train_Acc	Train_F1 score	Val_Loss	Val_Acc	Val_F1 score
1	0.6320	0.7188	0.5324	0.6067	0.7750	0.4366
2	0.5688	0.7875	0.4406	0.5537	0.8000	0.4444
3	0.5117	0.8063	0.4464	0.5175	0.8000	0.4444
4	0.4896	0.8125	0.4792	0.4893	0.8000	0.4444
5	0.4659	0.8063	0.4464	0.4653	0.8000	0.4444
. . .	. . .	. . .	. . .	. . .	. . .	. . .
96	0.0318	0.9938	0.9901	0.3515	0.9250	0.8622
97	0.0271	1.0000	1.0000	0.3517	0.9000	0.8039
98	0.0261	1.0000	1.0000	0.3540	0.9000	0.8039
99	0.0211	1.0000	1.0000	0.3533	0.9250	0.8622
100	0.0384	0.9812	0.9704	0.3571	0.9250	0.8622

From the above Table 3, it is evident that the initial accuracy value gained was 77.5% with loss and 60.67% and 43.66% as validation F1-scores. The improvement rapidly increased at the 2nd epoch and reached 80%. At the 14th epoch, the accuracy increased to 90%, and at the 18th epoch, the model achieved 92.50% accuracy. The accuracy fluctuated from 90% to 92.50% until the last epoch runs and remained at 92.50% at the 99th and 100th epochs, respectively. Thus, it is inferred that the validation F1-score at the 100th epoch was 86.22%, with an accuracy of 92.50% and loss at 35.71% (refer to figure 4 and figure 5).

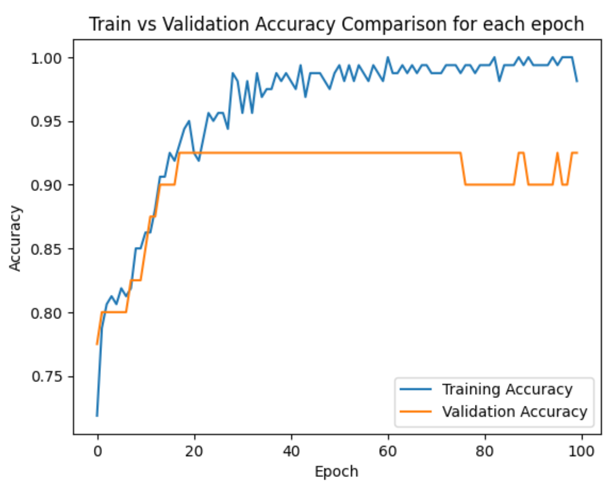

Figure 4.
Base model – Accuracy analysis.

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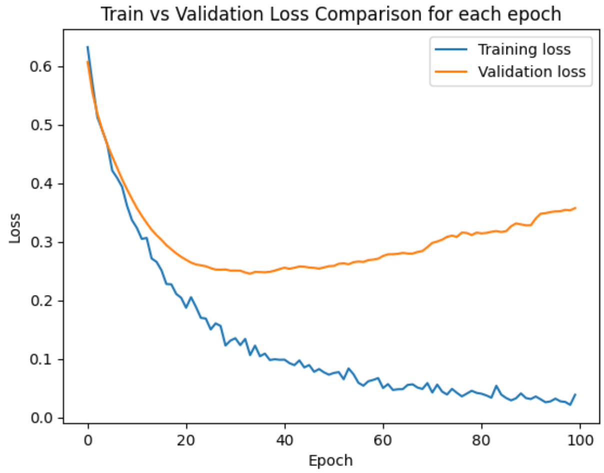

Figure 5.
Base model – Loss analysis.

From figures 4 and 5, it is interpreted that the accuracy increased rapidly with a decrease in the loss value from 0.6 to 0.3. However, the model shows overfitting with a higher F1-score during training (97.04%) and less during validation (86.22%). To address this, in the DCNN-SMH model, early stopping with fine-tuning of the learning rate (lr) is implemented.

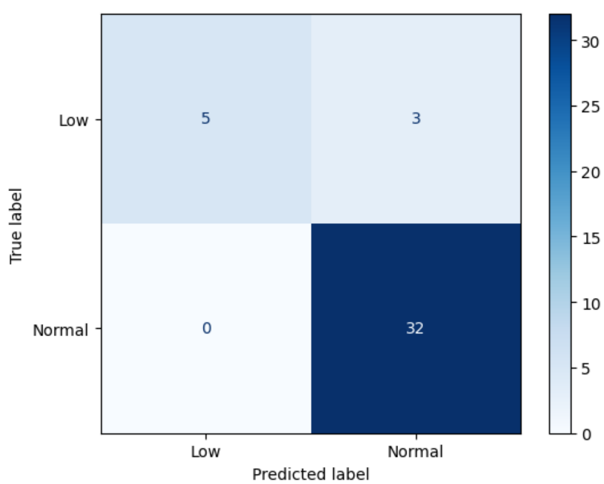

Figure 6.
Confusion matrix – Base model.

The confusion matrix for the classification (Normal: 1 and Low: 0) in the above figure (refer to Figure 6) shows that the performance metrics obtained are: precision is 100%, recall rate is 62.5%, F1-score is 76.92%, with an accuracy of 92.50% (refer to Table 4).

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Table 4.
Classification report of Base model.

	Precision	Recall	F1-Score	Support
0	1.00	0.62	0.77	8
1	0.91	1.00	0.96	32
accuracy			0.93	40
macro avg	0.96	0.81	0.86	40
weighted avg	0.93	0.93	0.92	40

Thus, the base model acquired the classification accuracy of 93% with a higher precision rate for class '0' and a recall rate for class '1', respectively.

4.2.2. DCNN-SMH Model

The training and validation of the advanced DCNN-SMH prediction model are carried out with 300 epoch runs, where the random state is set at 42. The batch size is kept at 16. To overcome the overfitting issue as the epoch runs increase, early-stopping technique is adopted to gain the best accuracy of the DL model. Similarly, ADASYN is added post-data splitting in training and validation sets for class imbalance. Here, the training shuffle is set to "True," while validation shuffle is set to "False." Few sample values from the actual data gained are given in Table 5.

Table 5.
Epoch values for DCNN-SMH model.

Epochs	Train_Loss	Train_Acc	Train_F1 score	Val_Loss	Val_Acc	Val_F1 score
1	0.6616	0.6786	0.6782	0.6440	0.8500	0.7849
2	0.6254	0.7976	0.7967	0.5870	0.8500	0.7403
3	0.5686	0.8373	0.8364	0.5402	0.8000	0.6875
4	0.4924	0.8611	0.8611	0.4909	0.7750	0.6639
5	0.4151	0.8690	0.8690	0.4297	0.8000	0.6875
.	.	.	.	.	.	.
.	.	.	.	.	.	.
116	0.0087	1.0000	1.0000	0.7131	0.9500	0.9134
.	.	.	.	.	.	.
.	.	.	.	.	.	.
96	0.0017	1.0000	1.0000	1.6794	0.8750	0.7365
97	0.0099	0.9960	0.9960	1.7487	0.8750	0.7365
98	0.0006	1.0000	1.0000	1.7699	0.8750	0.7365
99	0.0005	1.0000	1.0000	1.7599	0.8750	0.7365
100	0.0091	0.9960	0.9960	1.6216	0.8750	0.7365

From Table 5, it is evident that the initial accuracy value gained was 85.00% with a loss of 0.64 and 64.40% and 78.49% as validation F1-scores. The accuracy fluctuated between 85% and 87.50% until the last epoch runs. It is inferred that the validation F1-score at the 100th epoch achieved 73.65%, with accuracy of 87.50% and loss at 1.6216%. The loss increased from 0.64 to 1.05 at the 129th epoch (refer to figures 7 and 8). The loss kept increasing up to 1.62; likewise, the accuracy and F1-scores kept fluctuating and decreasing as the epoch runs increased. Hence, the best accuracy and validation F1-scores are considered the best output.

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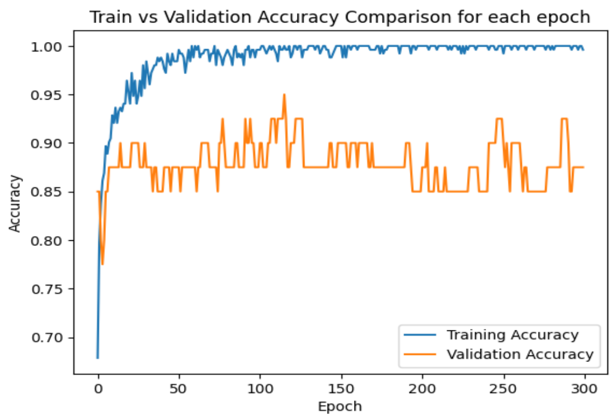

Figure 7.
Advanced DCNN-SMH model – Accuracy analysis.

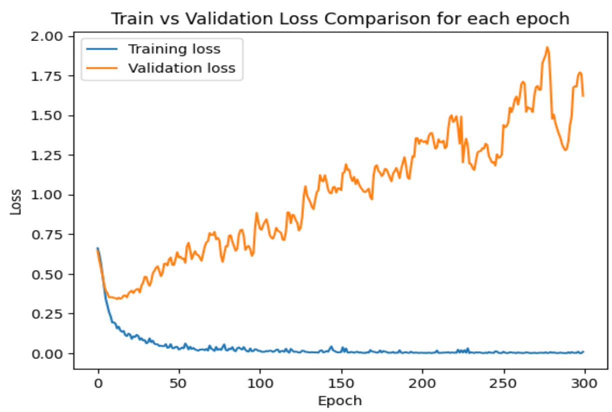

Figure 8.
Advanced DCNN-SMH model – Loss analysis.

From Figures 7 and 8, it is understood that the accuracy increased and the loss decreased rapidly in the advanced DCNN-SMH prediction model compared to the base model. The best accuracy obtained from the DCNN-SMH model was at the 116th epoch, with an accuracy of 95.00% and an F1-score of 91.34%.

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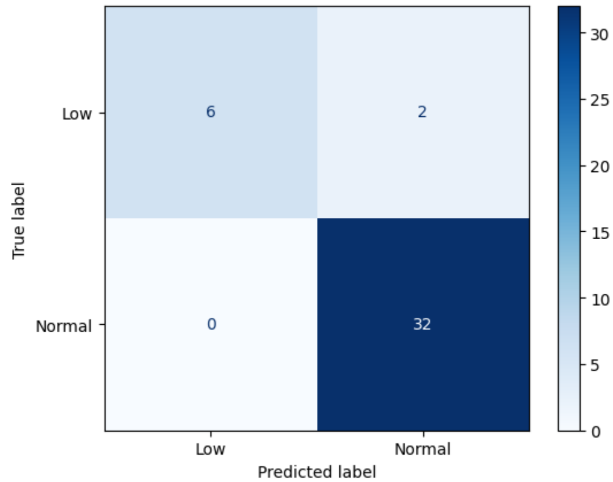

Figure 9.
Confusion matrix – DCNN-SMH prediction model.

The confusion matrix (refer to figure 9) shows that the difference in the prediction of the DCNN-SMH model from the base model improved accuracy, as depicted in Table 6.

Table 6.
Classification report of DCNN-SMH model.

	Precision	Recall	F1-Score	Support
0	1.00	0.75	0.86	8
1	0.94	1.00	0.97	32
accuracy			0.95	40
macro avg	0.97	0.88	0.91	40
weighted avg	0.95	0.95	0.95	40

The classification accuracy of the DCNN-SMH prediction model is 95%, with a higher precision rate for class '0' and a higher recall rate for class '1'. Although the classification outcomes of both models are similar, the advanced dense-net model (DCNN-SMH) achieved 2% higher accuracy than the base model, indicating that the developed linear-sequential model with seven layers is more accurate.

4.2.3. Comparison of Models Via Performance Metric Evaluation

This section compares a few existing research studies that used deep learning models in machine learning. The performance of the developed models is compared by evaluating the metric values obtained for classification from both DL models, as depicted in table 7, to identify the best model.

Table 7.
Performance analysis of both DL models.

	Class	Precision	F1-score	Recall	Accuracy
Base model	0	100	62	77	93
	1	91	100	96	
Advanced DCNN-SMH model	0	100	86	75	95
	1	94	97	100	

Interpretation: The precision for class '0' is higher in both models, whereas the F1-score is highest in the base model, and the recall rate is highest in the advanced model.

The accuracy rates of the deep learning prediction models are compared to identify the best prediction model (refer to figure 10).

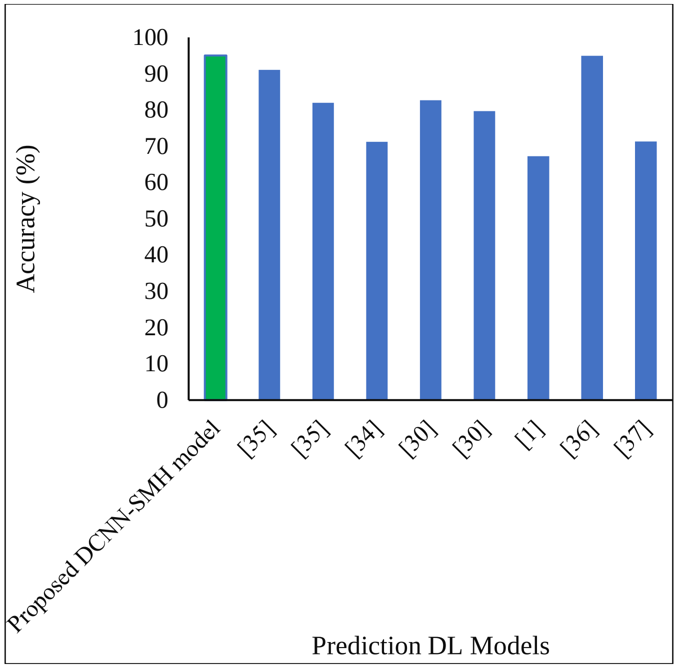

Figure10.
Comparative analysis of maternal health prediction models.
Source: Pi, et al. [26]; Agbeyangi and Lukose [27]; Pavagada and Vemuri [28]; Al Mashrafi, et al. [1] and Togunwa, et al. [29].

From Figure 10, it is visible that the proposed model gained higher accuracy (95%), followed by the ANN model with 94.88%, which is nearer to the current research outcome. Other deep learning models gained less accuracy in predicting risks in maternal health. It is also to be noted from the figure that the lack of DL models in maternal health predictions paves the way for the current research, which also makes it complicated to compare with more similar purpose research. Thus, the proposed research will provide insight and knowledge for using deep learning-based maternal health prediction models.

The proposed research explores maternal health using the dataset with parameters age, blood_pressure_systolic, blood_pressure_diastolic, haemoglobin_level, pre_pregnancy_bmi, gestational_age_weeks, number_of_prenatal_visits, has_hypertension, has_diabetes, smoking_status, education_level, alcohol_consumption, iron_supplementation, household_income, and birth_weight_category (target: output). The risks during pregnancy vary, including hypertension (eclampsia and pre-eclampsia), diabetes, infections (after childbirth), severe bleeding (post-delivery or during pregnancy), and other serious complications that can lead to obstructed labor [30, 31]. Poor mental health, along with prolonged physical health issues, also leads to maternal health risks resulting in stillbirth. Risking both mother's and child's health and life can be prevented using prediction models [32]. The machine models predict risks using parameters that prevent mortality and morbidity rates [33].

Existing studies Asad, et al. [34]; Khadidos, et al. [35]; Li, et al. [36] and Koivu and Sairanen [37] on maternal health prediction used decision trees, random forest, Gaussian models, logistic regressors, kNN, SVM (support vector machines), Naïve Bayes (NB), gradient boosting machines, ANN, CNN, and RNN. However, the networking layers used in the models differ according to the datasets and the purpose proposed.

5. Conclusions

In this research, a multilayer neural network with dense layers has been adopted. A basic deep neural network (dNN) in multilayer form has three connected layers, where the input layer along with one or

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more hidden layers are used. The base prediction model employing the dense network has one input layer with four dense-sequential layers and one output layer, totaling five layers. When tested using datasets (Training: Testing = 80:20), this model achieved an 86.22% F1-score rate with a 92.50% accuracy rate. Simultaneously, the research developed an advanced dense network model with seven layers, including three additional layers of ReLU, linear, and dropout layers. To improve prediction accuracy, the learning rate was fine-tuned to 0.001, and Adam optimization was adopted. Additionally, to address overfitting issues as epochs increased (from 100 to 300), the model was trained with early stopping to capture the best accuracy and F1-score. The advanced dense network achieved a higher accuracy of 95% and an F1-score of 91.34%. The outputs were classified into pre-defined labels: “Normal” and “Low,” for classifying the child's birth weight (target). By examining maternal health, risks at birth can be mitigated through prior medical precautions. The classification accuracy of the base model was recorded at 93%, whereas the advanced multi-layer dense network model (DCNN-SMH) achieved 95%. From these results, it is concluded that when machine learning, deep learning, ensemble, and hybrid models are fine-tuned, they produce more accurate outcomes than DCNN, RNN, and ANN models. In this study, the base model predicted less accurately than the advanced dense neural network model. The classification accuracy was also higher in the DCNN-SMH model compared to the base model.

Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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References
[1] S. S. Al Mashrafi, L. Tafakori, and M. Abdollahian, "Predicting maternal risk level using machine learning models," *BMC Pregnancy and Childbirth*, vol. 24, p. 820, 2024. https://doi.org/10.1186/s12884-024-07030-9
[2] R. Ramakrishnan, S. Rao, and J.-R. He, "Perinatal health predictors using artificial intelligence: A review," *Women's Health*, vol. 17, p. 17455065211046132, 2021. https://doi.org/10.1177/17455065211046132
[3] Ö. Dülger, A. Dursun, and U. Ö. Osmanoğlu, "Fetal birth weight estimation with machine learning techniques in 15–40 weeks of pregnancy," *Van Medical Journal*, vol. 31, no. 3, pp. 186–191, 2024. https://doi.org/10.5505/vmj.2024.09797
[4] A. I. Naimi, R. W. Platt, and J. C. Larkin, "Machine learning for fetal growth prediction," *Epidemiology*, vol. 29, no. 2, pp. 290-298, 2018. https://doi.org/10.1097/EDE.0000000000000788
[5] I. N. Margret and K. Rajakumar, "A meta-analysis of machine learning models in pregnancy care and applications," in *2024 10th International Conference on Communication and Signal Processing (ICCSP) (pp. 1521-1526). IEEE*, 2024.
[6] U. K. Lilhore *et al.*, "Prevalence and risk factors analysis of postpartum depression at early stage using hybrid deep learning model," *Scientific Reports*, vol. 14, p. 4533, 2024. https://doi.org/10.1038/s41598-024-54927-8
[7] X. Lin, C. Liang, J. Liu, T. Lyu, N. Ghumman, and B. Campbell, "Artificial intelligence–augmented clinical decision support systems for pregnancy care: Systematic review," *Journal of Medical Internet Research*, vol. 26, p. e54737, 2024. https://doi.org/10.2196/54737
[8] S. Venkatasubramanian, "Ambulatory monitoring of maternal and fetal using deep convolution generative adversarial network for smart health care IoT system," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 1, pp. 214-222, 2022.
[9] P. Karmakar, M. S. Hossain, R. Islam, and M. Hasan, "Automated pregnancy risk level prediction using advanced machine learning and deep learning algorithm," *International Journal of Computer Applications*, vol. 975, p. 8887, 2025.

[10] H. Sufriyana *et al.*, "Comparison of multivariable logistic regression and other machine learning algorithms for prognostic prediction studies in pregnancy care: Systematic review and meta-analysis," *JMIR Medical Informatics*, vol. 8, no. 11, p. e16503, 2020. https://doi.org/10.2196/16503

[11] D. Zhang, C. Yin, J. Zeng, X. Yuan, and P. Zhang, "Combining structured and unstructured data for predictive models: A deep learning approach," *BMC Medical Informatics and Decision Making*, vol. 20, p. 280, 2020. https://doi.org/10.1186/s12911-020-01297-6

[12] L. Vasudevan *et al.*, "Machine learning models to predict risk of maternal morbidity and mortality from electronic medical record data: Scoping review," *Journal of Medical Internet Research*, vol. 27, p. e68225, 2025. https://doi.org/10.2196/68225

[13] A. Sharma, J. Malhotra, S. Sharma, M. Grover, and Shruti, "Predicting maternal health risk using machine learning models and comparing the performance of percentage split and K-fold cross validation," *International Journal of Novel Research and Development*, vol. 9, no. 5, pp. 804–811, 2024.

[14] S. Hemalatha and V. Maria Anu, "A smart auto-encoded dense birth predictor with social cognitive optimization model for accurate childbirth mode prediction," *International Journal of Intelligent Engineering and Systems*, vol. 18, no. 9, pp. 88–105, 2025. https://doi.org/10.22266/ijies2025.1031.07

[15] L. Pawar, J. Malhotra, A. Sharma, D. Arora, and D. Vaidya, "A robust machine learning predictive model for maternal health risk," in *2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC) (pp. 882-888). IEEE*, 2022.

[16] J. Gao *et al.*, "Fetal birth weight prediction in the third trimester: Retrospective cohort study and development of an ensemble model," *JMIR Pediatrics and Parenting*, vol. 8, p. e59377, 2025. https://doi.org/10.2196/59377

[17] R. D. Henry, "Predicting newborn birth outcomes with prenatal maternal health features and correlates in the United States: A machine learning approach using archival data," *BMC Pregnancy and Childbirth*, vol. 24, p. 603, 2024. https://doi.org/10.1186/s12884-024-06812-5

[18] D. A. Alabbad *et al.*, "Birthweight range prediction and classification: A machine learning-based sustainable approach," *Machine Learning and Knowledge Extraction*, vol. 6, no. 2, pp. 770-788, 2024. https://doi.org/10.3390/make6020036

[19] P. Keerthana and S. B. Suvanam, "Prediction of birth weight using machine learning models," *International Journal of Engineering Trends and Technology*, vol. 73, no. 4, pp. 440–452, 2025. https://doi.org/10.14445/22315381/IJETT-V73I4P136

[20] A. Ranjbar, F. Montazeri, M. V. Farashah, V. Mehrnoush, F. Darsareh, and N. Roozbeh, "Machine learning-based approach for predicting low birth weight," *BMC Pregnancy and Childbirth*, vol. 23, no. 1, p. 803, 2023. https://doi.org/10.1186/s12884-023-06128-w

[21] M. Mursil *et al.*, "Interpretable deep neural networks for advancing early neonatal birth weight prediction using multimodal maternal factors," *Journal of Biomedical Informatics*, vol. 166, p. 104838, 2025. https://doi.org/10.1016/j.jbi.2025.104838

[22] M. Pavanya, K. Chadaga, A. Vasudeva, B. K. Rao, S. Prabhu, and S. K. Bhat, "Prediction of birthweight with early and mid-pregnancy antenatal markers utilising machine learning and explainable artificial intelligence," *Scientific Reports*, vol. 15, p. 26223, 2025. https://doi.org/10.1038/s41598-025-11837-7

[23] S. A. Alzakari, A. Aldrees, M. Umer, L. Cascone, N. Innab, and I. Ashraf, "Artificial intelligence-driven predictive framework for early detection of still birth," *SLAS Technology*, vol. 29, no. 6, p. 100203, 2024. https://doi.org/10.1016/j.slast.2024.100203

[24] T. B. Reza and N. Salma, "Prediction and feature selection of low birth weight using machine learning algorithms," *Journal of Health, Population and Nutrition*, vol. 43, p. 157, 2024. https://doi.org/10.1186/s41043-024-00647-8

[25] Ziya, "Maternal health features dataset," 2025. https://www.kaggle.com/datasets/ziya07/maternal-health-features-dataset

[26] X. Pi, J. Wang, L. Chu, G. Zhang, and W. Zhang, "Prediction of high-risk pregnancy based on machine learning algorithms," *Scientific Reports*, vol. 15, no. 1, p. 15561, 2025. https://doi.org/10.1038/s41598-025-00450-3

[27] A. Agbeyangi and J. Lukose, "Sustainable IoT-enabled predictive analytics for maternal health risk prediction: A deep learning approach," *International Journal of Innovative Research and Scientific Studies*, vol. 8, no. 2, pp. 409–419, 2025. https://doi.org/10.53894/ijirss.v8i2.5189

[28] K. Pavagada and J. Vemuri, "Prediction of maternal health risk factors using machine learning algorithms," *Procedia Computer Science*, vol. 258, pp. 2713-2722, 2025. https://doi.org/10.1016/j.procs.2025.04.532

[29] T. O. Togunwa, A. O. Babatunde, and K.-u.-R. Abdullah, "Deep hybrid model for maternal health risk classification in pregnancy: Synergy of ANN and random forest," *Frontiers in Artificial Intelligence*, vol. 6, p. 1213436, 2023. https://doi.org/10.3389/frai.2023.1213436

[30] K. D. Tzimourta, M. G. Tsipouras, P. Angelidis, D. G. Tsalikakis, and E. Orovou, "Maternal health risk detection: Advancing midwifery with artificial intelligence," *Healthcare*, vol. 13, no. 7, p. 833, 2025. https://doi.org/10.3390/healthcare13070833

[31] D. Mennickent *et al.*, "Machine learning applied in maternal and fetal health: A narrative review focused on pregnancy diseases and complications," *Frontiers in Endocrinology*, vol. 14, p. 1130139, 2023.

[32] U. Sirisha *et al.*, "Dynamic multi-layer perceptron for fetal health classification using cardiotocography data," *Computers, Materials & Continua*, vol. 80, no. 2, pp. 1-30, 2024.

[33] C. Gao, S. Osmundson, D. R. V. Edwards, G. P. Jackson, B. A. Malin, and Y. Chen, "Deep learning predicts extreme preterm birth from electronic health records," *Journal of Biomedical Informatics*, vol. 100, p. 103334, 2019. https://doi.org/10.1016/j.jbi.2019.103334

[34] A. Asad, M. Sarwar, M. Aslam, E. Akpokodje, and S. F. Jilani, "MultiScaleFusion-net and resrnn-net: Proposed deep learning architectures for accurate and interpretable pregnancy risk prediction," *Applied Sciences*, vol. 15, no. 11, p. 6152, 2025. https://doi.org/10.3390/app15116152

[35] A. O. Khadidos, F. Saleem, S. Selvarajan, Z. Ullah, and A. O. Khadidos, "Ensemble machine learning framework for predicting maternal health risk during pregnancy," *Scientific Reports*, vol. 14, no. 1, p. 21483, 2024.

[36] X. Li, Y. Lu, X. Fu, and Y. Qi, "Building the Internet of Things platform for smart maternal healthcare services with wearable devices and cloud computing," *Future Generation Computer Systems*, vol. 118, pp. 282-296, 2021.

[37] A. Koivu and M. Sairanen, "Predicting risk of stillbirth and preterm pregnancies with machine learning," *Health Information Science and Systems*, vol. 8, no. 1, p. 14, 2020. https://doi.org/10.1007/s13755-020-00105-9