Collating Random Forest Classifier and Artificial Neural Networks for the Risk Detection of Maternal Health

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Abstract— **This paper compares the performance of ANN models to Random Forests on benchmarking a test dataset against the risk levels of maternal health as low, mid, or high. The features considered are clinical features, namely age, blood pressure, and heart rate. The dataset was imbalanced and needed adapting the ANN architecture by fitting class weights and dropout regularization. The best test accuracy obtained in this fashion was 73%. As the ANN had learned many of the complex data patterns in the dataset, it was, however, still limited by the moderate size and skewness of the dataset. The Random Forest model with grid search produced a much better accuracy of 85.71% compared with ANN, thereby suggesting relatively high generalization across all the classes for better minority risk level classes. An ensemble approach of the Random Forest method appears to better serve toward high accuracy along with interpretability for clinical decision support in maternal health risk assessment.**

Keywords—Maternal health, ANN, Random forest, risk, Keras.

I. INTRODUCTION

Pregnancy is a delicate and beautiful process that requires care and quite a lot of monitoring of all the processes that directly or indirectly affect it. From the prehistoric era to the modern world, though the methods of delivery may have changed, the scenario hasn't. For example, the risks involved during pregnancy remained the same. The risks for every maternal woman differ from person to person, but if there are some patterns in these cases and if they are extracted then we would certainly know the risk factors or could predict the risk level for every pregnant woman. The risks involved during pregnancy and delivery of the baby are serious concerns for the family of the respective woman and we all may face this at some point in our life. Doctors aren't able to figure out the solutions for the complications during pregnancy. Obstetricians are the branch of doctors that deals with pregnancy & childbirth-related cases. A good obstetrician is essential for the smooth delivery of a baby. Imagine what if the obstetrician or the gynecologist that a certain pregnant woman is consulting for the unwrinkled process of delivery isn't qualified [1]. According to the Indian Express, possibly about 35,000 Obstetricians or gynecologists in India aren't registered with the, 'Federation of Obstetrics and Gynecological Societies of India' (FOGSI). Hence, the risk factors that should be identified well before the delivery and treated timely, aren't executed. Risk factors for any pregnant woman are the decisive aspect as finding them on time is important and treating them as well. These risk factors include high blood pressure, asthma, obesity, consuming alcohol, smoking, cholesterol levels, etc. These factors decide the health of the pregnant woman & treating them on time decides the level of complications that she or her baby may face.

All the levels of risk factors vary from woman to woman and their conditions also differ every time hence doctors can't predict the surety of risk level that women may face [2]. In the modern era where technology has advanced and every and all amount of data that we demand is available to us, we all tend to solve these problems. Machine Learning learning and deep learning are the two essential techniques that handle huge data appropriately, process them faster, and discover results accurately. Basically, we need a method to predict whether a pregnant woman with certain risk factors may have a threat during delivery or not [3].

The main task of artificial intelligence is not to reduce human efforts, but to enhance the results bringing more precision to those tasks that humans couldn't do at a good rate of time or accurately. This is the true need for AI in healthcare as this is a serious issue that needs to be addressed on a high scale. Withthe help of data analysis, dashboards could be made for those pregnant women

whom the ML or DL model has predicted as high risk, for their personalized treatment and asses them more nicely.

II. RELATED WORKS

Research predicting maternal health has examined data from various hospitals and clinics. This data includes blood pressure (both systolic and diastolic), blood sugar levels, body temperature, age, heart rate, and risk levels. Some methods that combine different techniques, like DR-BiLTCN (which uses decision trees and support vectors together), can be very accurate - up to 98% [4]. Other studies have checked out machine learning methods that learn from examples such as k-Nearest Neighbor and Random Forest. These studies used data about blood pressure when the baby was delivered, the mother's age how many pregnancies she's had, and her heart health. These methods were able to get it right up to 95% of the time [5], [6].

Researchers have put Random Forest to good use in looking at healthcare trends with the Nationwide Inpatient Sample (NIS) getting it right about 88.79% of the time [7]. They've dug deeper into things that can affect moms and babies, like stillbirth, to better grasp the key terms and methods in this field [8]. Also, scientists have taken a long hard look at Artificial Neural Networks (ANN) to see how well they can mimic the tricky relationships in health data. These ANNs, which are made up of fake brain cells hooked up in layers, have found their way into solving all sorts of real-world data puzzles [9], [10].

For example, studies [11], [12], and [13] showed Random Forest works well with uneven datasets and gives clearer results when sorting risks during pregnancy. Research by [14] brought in AI models you can understand showing how important this is in medical settings. In the same way, work in [15] looked at old statistical methods next to ML models proving ML does better at predicting risks of heavy bleeding after birth. Studies [16] and [17] looked into mixed models that use ANN and Random Forest together getting better accuracy and speed when sorting maternal risks. At the same time, [18] made a system to spot pregnancy risks that went beyond Random Forest adding in mental health factors. New research, like [19] and [20], talked about using many types of data sources and new datasets like OxMat leading to strong AI tech in mother and baby health. In the end, these steps forward show how AI and ML are changing aiming to improve mother's health outcomes with reliable tools that make predictions you can understand.

III. METHODOLOGY

Considering the fact that the complications associated with maternal health have very serious consequences in terms of health, proper categorization of risk levels into three-low, medium, and high-and at the clinical parameter level is desirable. This can help the health practitioners identify at-risk cases at an early stage so interventions might be attempted in time to save lives. To this end, we use ANN as well as a machine learning model, Random Forest, on a judiciously selected dataset of clinical variables to classify the risk levels for maternal health. This will enable us to

compare the advantages and disadvantages of each type of model within this classification task and gain insight into practical applicability in the context of maternal healthcare risk prediction.

The dataset of the present study contained clinical features relevant to maternal health, namely Age, SystolicBP, DiastolicBP, BS-bloodo sugar levels, HeartRate, and BodyTemp. Such features are well known to determine maternal health conditions and are usually checked in pregnancies. The target variable, RiskLevel, categorizes the patients into three distinct classes: low, medium, and high risk. This is a multiclass classification problem that would be appropriate for both ANN and Random Forest models but presents some technical considerations. The first issue with the dataset in question is related to class imbalance-class imbalance means that there is an unbalanced number of classes in proportion. More precisely, the cases of low risk occur considerably more frequently than the medium and high-risk cases. To overcome this, we implemented class weights for the Random Forest and used class balancing techniques such as SMOTE (where applicable) so that both ANN and Random Forest models are trained to view the data in a balanced manner. Additionally, we preprocessed the data through scaling of features to improve the performance of the ANN model.

We have used both ANN and Random Forest models in an attempt to compare which one will be able to perform better on this classification task. The ANN is a particularly powerful deep learning model that will be able to learn complex, non-linear relationships between different features-and there can be nothing more empirically fruitful than this for healthcare data, where interactions among clinical factors so often critically impact outcomes. However, the effect of an ANN is that it generally requires large datasets and careful tuning to avoid overfitting, meaning that it is computationally intensive. In contrast, Random Forest is the robust and interpretable model in machine learning that constructs an ensemble of decision trees for prediction. It is well known for its ability to well handle datasets of sizes from small to medium sizes, and also handles imbalanced data very well. It is able to provide insights into the importance of features; thus, it will be an appropriate choice. Given that our dataset is relatively modest in size, the alternative for us would be Random Forest to cope with the noise in the data while providing interpretable results with less risk of overfitting than deep learning models.

Such a comparison of ANN against Random Forest allows for a cross-analysis of performance trade-offs and dictates the requisites for selecting deep learning and machine learning approaches in maternal health risk classification. This comparison is important because it showcases the capacities and limitations of both models, providing useful insights for healthcare professionals and data scientists who handle identical data. For instance, although ANN may perform better in certain cases, the interpretability and efficiency of Random Forest make this model a good contender for clinical deployment when model interpretability is of importance. In that sense, this work contributes to the field by outlining and determining which

type of model would best classify risk across different conditions to aid in the successful development of reliable and actionable predictive tools in maternal healthcare.

A. ANN

The ANN model as shown in table 1 is built using the Keras Sequential API and consists of multiple dense layers, including ReLU activation and dropout layers to prevent overfitting. The architecture is as follows: AI Check here.

TABLE I. ANN MODEL SUMMARY

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 64)	448
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 128)	8320
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 64)	8256
dropout_2 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 32)	2080
dense_4 (Dense)	(None, 3)	99
Total params: 19,203 Trainable params: 19,203 Non-trainable params: 0		

The model starts with an input layer set to 64 units and ReLU activation. It has been selected due to its capability to introduce non-linearity and correct the vanishing gradient issue, which made it capable for working on deep neural networks. Each dense layer is followed by a dropout layer that is set at a rate of 0.3; that is, for each training epoch, 30% of the neurons are randomly disabled. That is, 30% of the neurons should be disabled during each training epoch. This dropout rate helps in avoiding overfitting as the model generalizes across the training data rather than memorizing them.

The final layer of the model is a dense layer with three units. This layer represents the three risk levels, namely high risk, low risk, and mid risk. In this case, the softmax activation function has been utilized. Softmax is a very important function in the multiclass classification environment as it produces a probability distribution across the three classes; hence, for any instance, the model can determine the most-likely risk category. The loss function is sparse_categorical_crossentropy, which gives a better fit for integer-encoded target classes, and the evaluation metric is accuracy.

Effective preprocessing of the data will be very important for the good performance of the ANN model, especially in this healthcare dataset since different features will have ranges and units. We first encoded the target variable, Risk Level, to the Label Encoding, which converts classes into integer labels: high risk = 0, low risk = 1, mid risk = 2. All the input features, Age, Systolic BP, Diastolic BP, BS, Body Temp, and Heart Rate are of different scales; therefore, Standard Scaler is used for standardization. Standardization implies that it brings the data to have a mean of 0 and a standard deviation of 1, and this allows stability to the optimization and accelerates the convergence speed by reducing the difference in range among features.
With preprocessing completed, the dataset was split into training and testing in order to use an 80-20 split, thus reserving part of the data for model evaluation, allowing us to gauge the generalization performance of the model on unseen samples.

The target variable in this dataset exhibits class imbalance as it comprises a greater number of high-risk instances over low-risk and mid-risk classes. Class imbalance can lead to the model's bias towards the majority class while ignoring the classification of the minority classes. In this study, we tackled class imbalance by applying class weights, whereby the classes with lesser occurrences would have higher values assigned over those with higher occurrences. The class weights were calculated based on the inverse frequency of each class to ensure that errors in predicting minority classes (e.g., high risk and mid risk) receive greater punishment than errors for the majority class. By applying class weights, we make the model more sensitive to the minority classes, improving performance metrics like recall and F1 score for those classes. The final classification report, however, revealed comparatively higher precision and recall scores for the high-risk class, thereby indicating that the model was successful in incorporating and prioritizing the high-risk category, given its smaller representation in the dataset.

This model was trained for up to 100 epochs with early stopping on validation loss: it stops the training if there's not an improvement at all for 10 consecutive epochs. Early stopping is a very important part of neural network training since it avoids overfitting by stopping the process as soon as the model stops generalizing better on the validation data. Training history shows that the model's training and validation accuracy progressively improved over the first few epochs as its loss reduces, which was a sign of learning success. During early epochs, accuracy gradually increasing from about 37% to the end, around 70% for both the training and validation sets. There could be fluctuations in validation accuracy and loss, which can be mainly due to layers of dropout, particularly complicated patterns in the data. However, at last, the model reached a test accuracy of around 73%, which proves that the model was capable enough to output proper classification under maternal health risk levels.

B. Random Forest

The Random Forest algorithm is well known as an ensemble learning approach that also happens to be robust, interpretable, and efficient-more so with classification tasks

on structured data. During training, it builds a number of decision trees, where each tree will be considered an individual "weak learner." Finally, the end classification will be determined by aggregating all predictions from the trees; this is typically done using majority voting. It reduces the high variance often reported for a single decision tree and hence improves generalization to unseen data. This will automatically reduce the class imbalance pertaining to the maternal health dataset. Class weighting applies more weighting to underrepresented classes, thereby limiting the chances that the classifier becomes biased towards the majority classes. This, coupled with the inherent ability of Random Forests to handle imbalanced data by averaging over many trees, makes it quite specifically a good application. Random Forest is less sensitive to class imbalance than most other machine learning methods, such as Support Vector Machines or k-Nearest Neighbors, even as its explicit class weighting serves to advantage.

The preprocessing pipeline for the Random Forest model begins with Label Encoding of the target variable Risk Level. It then directly maps classes into integer values: high and low risk are mapped onto the numbers 0 and 1, mid risk is put onto number 2, which is necessary if targeting a supervised learning task where such numerical value is considered necessary for the classification by the model. We then standardized the input features: Age, Systolic BP, Diastolic BP, BS, Body Temp, and Heart Rate using Standard Scaler. Although Random Forest models do not, in fact, rely on feature scaling, like algorithms based on distance calculation do, scaling sometimes can be useful here to ensure that all features are similarly weighted; it is particularly relevant when cross-validating with other algorithms that require scaling. The dataset was split into a training set and a test set using an 80-20 split, so we could check the model's generalization on unseen data.

Target variable class imbalance may further influence the power of the model in correct classification of the minority classes, especially since our classes are not well distributed. The weight is adjusted inversely proportional to class frequencies, so misclassifications will be weighed more heavily for classes poorly represented with more risk and mid risk. This technique permits the classifier to dynamically set the weights such that it is inherently better prepared for dealing with all classes and ultimately detects cases from the minority classes. Class balancing in Random Forests is automated, hence a greater penalty per split for the particular minority class at each split of each single tree is assigned to preserve representative splits. This approach has proven to be highly effective, as evidenced by the classification report and final model accuracy, where the risk classes achieved reasonable recall and precision, thus resulting in a high degree of balance in class treatment.

Hyperparameter tuning was essential in Random Forest models, since parameters like the number of trees (n_estimators), maximum tree depth (max_depth), minimum samples required for a split (min_samples_split), and minimum samples per leaf (min_samples_leaf) are quite influential. Based on a grid search, we tested a combination of hyperparameters with 5-fold cross-validation. This exhaustive search evaluates various parameter combinations, selecting the one that maximizes cross-validated accuracy.

The parameter grid was defined as follows:

1. **n_estimators**: [100, 200, 300] – varying the number of trees helps determine the ideal balance between model complexity and computational efficiency.
2. **max_depth**: [None, 10, 20, 30]-this hyperparameter avoids overfitting via tree complexity.
3. **min_samples_split**: [2, 5, 10]-this is the minimum samples required to allow a node to be split into different parts; thus, higher values will yield simpler trees.
4. **min_samples_leaf**: [1, 2, 4]-it affects the minimum, causing splits that are too specific.

The use of grid search with cross-validation to select parameters was to check the degree of generalization of the corresponding accuracy scores across different data partitions. Following cross-validation, the combination of parameters that gave the best results were employed to fit the final Random Forest model on the whole training data set.

We fitted it onto the training data and checked the test set once the model was trained with the best parameters. The Random Forest model had a test accuracy of 85.71%. This was significantly higher as compared to the corresponding 73% accuracy achieved by the ANN model. It could be attributed to the following reasons:

1. Unlike ANNs, which often require huge datasets with careful regularization against overfitting, Random Forests are intrinsically robust even when using small to medium-sized structured datasets. In this application, the ensemble nature of the algorithm allowed Random Forest to expose complex patterns in the data without overfitting and hence produced better generalization.

2. Feature Importance and Interpretability: Random Forest features the importance of feature attribution, which allowed us to understand which clinical features significantly contributed to maternal health risk prediction. Such interpretability is very advantageous for healthcare applications where understanding the model's decision-making is critical.

3. Balance Treatment of Classes: Balancing class problem was far better treated in the model by the application of class_weight = "balanced." This helped in enabling the model to identify cases both from minority classes. This resulted in the model to have a high recall and precision for the two classes as reflected in the classification report.

IV. RESULTS

Our maternal health risk classification task does indeed differ in the characteristics of performance by each model. In using multiple dense layers with dropout for regularization and having an accuracy of 73%, the ANN model is outperformed significantly by the Random Forest model, which reached an accuracy of 85.71%. It goes on to illustrate

how ensemble-based approaches like Random Forest can even benefit from structured datasets with moderate complexity. Further inspection by graphical analysis of the training and validation loss and accuracy curves yields additional insights as shown in the figures 1, 2, 3 and 4. Learning curves for ANN model represented fluctuation in validation accuracy and loss, indicating slight overfitting due to the dropout layers because the model was unable to generalize beyond the training set. In comparison, Random Forest has stable accuracy at cross-validation; therefore, its general performance is more consistent in its test samples.
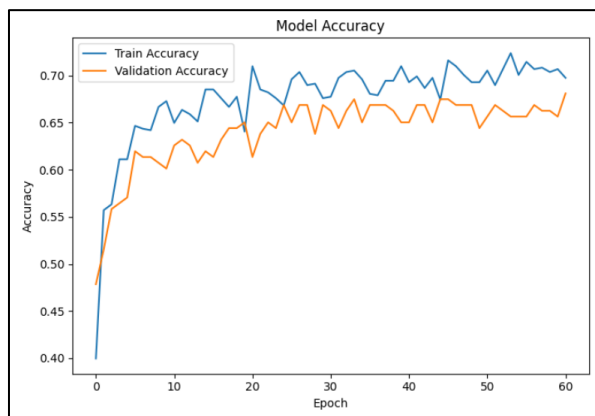

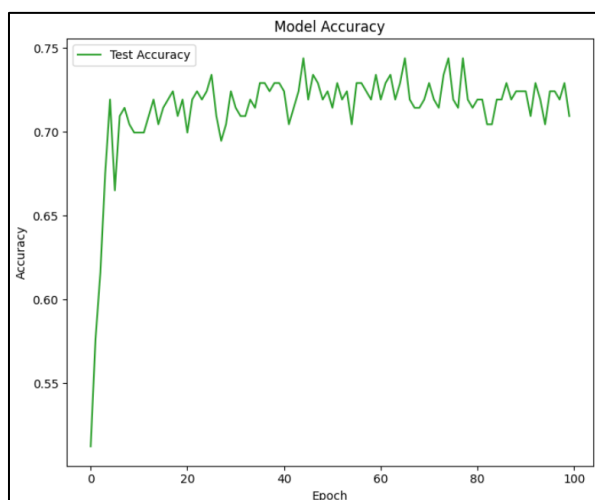Fig. 1 ANN Training Accuracy.

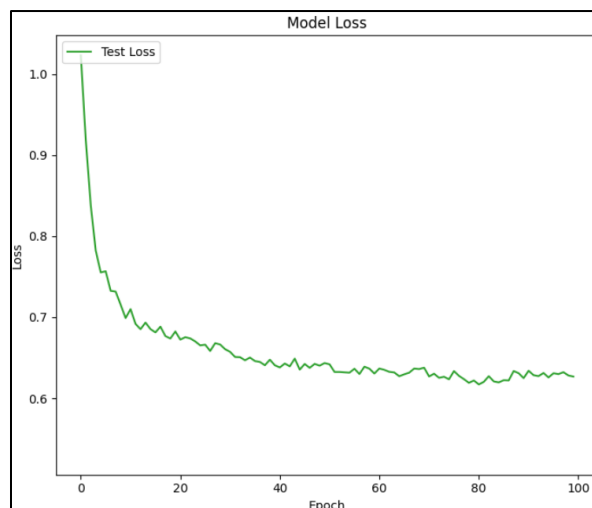Fig. 2 ANN Training Loss.

Fig. 3 ANN Testing Accuracy.

Fig. 4 ANN Testing Loss

As both models depict a classification report as shown in the figures 5 and 6, the Random Forest model is seen to have very evenly distributed precision, recall, and F1-scores for all classes. For instance, in class high risk, the recall had actually been better than the model of ANN, thereby identifying more true cases as high risk. It was particularly hard in the mid-risk class because feature distributions of this class overlap hugely with the other classes, yet the Random Forest model does expose a recall improvement of the ANN, demonstrating its robustness to the minority classes, helped in turn by the usage of class_weight="balanced".

	precision	recall	f1-score	support
high risk	0.75	0.89	0.82	55
low risk	0.69	0.84	0.76	81
mid risk	0.69	0.40	0.51	67
accuracy			0.71	203
macro avg	0.71	0.71	0.69	203
weighted avg	0.71	0.71	0.69	203

Fig. 5 ANN Classification Report.

	precision	recall	f1-score	support
high risk	0.85	0.91	0.88	55
low risk	0.88	0.85	0.87	81
mid risk	0.83	0.82	0.83	67
accuracy			0.86	203
macro avg	0.86	0.86	0.86	203
weighted avg	0.86	0.86	0.86	203

Fig. 6 Random Forest Classification Report.

The confusion matrices as shown in the figure 7, further expose these differences. For ANN, mid risk was largely confused with other classes. This ANN model seems more inclined to put some cases in the low risk class. This can most likely be attributed to the greater variance of the ANN model and its higher sensitivity with regard to feature scaling. On the contrary, with Random Forest's confusion matrix having fewer misclassifications, particularly in distinguishing high-risk from low-risk and also mid-risk, it could support the idea of ensemble voting in the separation of classes.
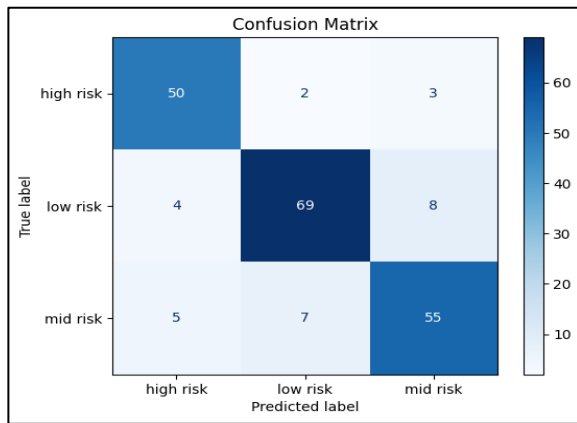
Fig. 7 Random Forest Confusion Matrix.

V. CONCLUSION

This paper provides a case study on the risk classification for maternal health using ANN and Random Forest models within a risk management framework. Even though the ANN was able to learn complex, non-linear patterns, the algorithm was limited due to a small number of samples and class imbalance as it attained a test accuracy of 73 percent only. Random Forest model on the other hand surpassed ANN as its test accuracy reached 85.71%, proving to be more robust, productive in relation to the problem of data imbalance as well as more interpretable. As each of those trees was based on different subsets of the input data, Random Forest provided reliable accuracy across the models and good balance of all the risk classes specifically the small ones. It can therefore be concluded that Random Forest has the best predictive performance for the clinical decision making process in maternal healthcare because it is efficient, consistent, requires little interpretation and is well suited for practice in situations where the amount of data and transparency of the model are the issues. It would be worthwhile to investigate combined approaches or use datasets with greater sample sizes to overcome the weaknesses identified in this work in the future.

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