# Prediction of Infertility Type in Women Via Stacked Ensemble Model

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# Prediction of Infertility Type in Women Via Stacked Ensemble Model

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**ABSTRACT**

This research shown the importance of implementing ensemble machine learning models for predicting women infertility in Nigerian and other geographical locations in the world. It analysed prevalent clinical risk factors that inclined women to infertility and confirmed the predictive accuracy of machine learning classifiers explored for the research.

These included Extreme Gradient Boosting (XGBoost), Extremely Randomized Trees (ExtraTrees) and Convolutional Neural Networks (CNNs). Dataset from two hospitals that had more than two decades of health records of women across Nigeria was used.

The data was gathered between 2012 and 2022. It contained information of 5,000 women, age between twenty-five and fifty-five years with twenty -six attributes. The factors were scrutinized to ascertain their predictive significance in identifying women at the risk of infertility via supervised machine learning classifiers.

**Keywords**: Infertility, Stacked Ensemble Model, Predictive Accuracy, Machine Learning Classifier Nigeria

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## Introduction

Infertility was a reproductive health disease that affected men and women across geographical zones of the world, including Nigeria community. Infertility was discovered when husband and wife failed to achieve pregnancy after 12 months of regular unprotected sexual intercourse [1][2]. When a woman had not experience pregnancy, her status was known as first degree infertility while a woman who have experienced pregnancy sometimes but was finding it difficult to achieve subsequent pregnancy had second degree infertility [3][4]. Infertility dataset was one of the large data accumulated in medical sciences in recent times. The data confirmed the present of clinical risk factors that inclined women to infertility [5]. Clinical risk factors were pre-existing health conditions that hindered effective functionality of human body[6]. They could occur in any part of the body but when emerged from the reprodcutive system of a woman, they post risk of infertility [7]. These factors could originate from ovulatory disorders, chromosome abnormalities, inherited single gene defect and lifestyle. Also, inactivity of other reproductive cells and infections were regarded as clinical risk factors [8-10]. There was a need for computer science intervention to predict infertility type in women so that each woman received treatment as individual from human expert. This was achievable by implementing supervised machine learning model on the clinical risk factors that associated women with infertility.

The availability of the large data on women infertility called for adoption of supervised machine learning models for predictive accuracy that complimented the objectives of Assisted Reproductive Technology (ART) on women infertility. Machine learning models were platforms capable of analaysing large dataset better than the traditional statistical models when large clinical dataset was considered [11][12]. Traditional statistical models were mathematical frameworks that enhanced the understanding of relationships between variables in small dataset. They depended on assumptions about data distribution and structure [13]. Analaysing the infertility dataset with supervised machine learning classifiers did not depend on absorption as traditional statistical methods but captured complex relationships among dataset that enhanced predictive accuracy, early diagnosis and personalized treatment plans. The analysis could assist human experts in decision making because it greatly reduced human errors and streamlined processes to improve patient outcomes. Also, supervised machine learning discovered new measures for diseases control and exposed hidden patterns which encouraged further research [14][15].

There were existing supervised machine learning predictive models for women infertility as revealed by the literature, but it was observed that there were gaps to fill. Dataset explored for the predictions were small and could not accurately represent all the clinical risk factors that inclined women to infertility in Nigeria and other geographical zones. The perspectives of the classifiers utilised were not capable of capturing patterns in the features available in the clinical risk factors that identified with women infertility. The performance evaluation metrics implemented were not efficient to prove the accuracy, interpretability and reliability of the models needed to predict infertility type in women [16-22]. The models were not generalizable on the real- world data of infertility. Medical sciences, especially reproductive medicine preferred clinical predictive models that their interpretability and generalizability were acceptable to both the users and human experts [23][24]. These advanced the objectivity of ART to personalize infertility treatment in women.

This research proposed to predict infertility type in women by developing a stacked ensemble machine learning model. A stacked ensemble model was a machine learning approach that combined the predictions of multiple base models, trained on the same dataset. It used a meta-model to produce a final prediction which improved accuracy and robustness. The base models were trained independently. Then, their predictions were used as input features for the meta-model, which learnt to optimize the final prediction by weighing the strengths of each base model.

The model developed harnessed the predictive power of two distinct machine learning models, these were eXtreme Gradient Boosting (XGBoost), Extremely Randomized Trees (Extra Trees) with one deep learning model known as Convolutional Neural Networks (CNNs).

## Statement of the Problem

Women with infertility challenge in Nigeria and other countries were faced with substantial emotional, psychological and financial obstacles. This was confirmed with a statistical report which highlighted that the fertility rate in Nigeria had dropped from 6.6 births per woman in 1973 to 5.1 births per woman in 2022[25]. This underscores the need for computer science intervention for early and accurate prediction of types of infertility in women.

There were existing predictive models as evidence of computer science intervention in prediction of women infertility, but the models could not solve the prediction challenge because of the following reasons:

The data set explored did not capture all the clinical risk factors that inclined women to infertility. Therefore, the model developed did not provide human experts with data driven insights that enhanced treatment decisions.

Also, there was problem with the applicability of the classifiers because they did not generalize as expected on unseen data.

They were unable to capture relationship patterns that could predictive infertility type in women.

These necessitate the development of an ensemble model that harnessed the predictive accuracy of three different classifiers. This engaged different perspectives of the classifiers to improve predictive accuracy of infertility type in women.

**Review of related works on Ensemble Machine learning predictive models for infertility in women**

Ensemble machine learning techniques have emerged as powerful tools for predictive modeling in various medical applications, including the prediction of infertility in women. These techniques, which combine multiple models to improve predictive accuracy and robustness, have been increasingly applied in the context of Assisted Reproductive Technology (ART) to enhance decision-making processes in clinical settings. Several closely related works have demonstrated the effectiveness of these approaches in addressing the complex challenge of infertility prediction, leveraging diverse datasets and methodologies to provide valuable insights into the factors influencing infertility and the success of treatment interventions.

[16] implemented an ensemble learning approach combined with outlier detection to predict the most appropriate infertility treatment for couples. Their study explored a dataset of 527 infertile couples, aiming to identify the best treatment method by analyzing the correlation between outlier samples and treatment outcomes. The use of ensemble learners in this context enhanced the prediction accuracy by integrating diverse perspectives from multiple models, thereby improving the overall reliability of the treatment recommendations. This study highlighted the importance of addressing outliers in medical data, which can significantly impact the performance of predictive models, particularly in the context of personalized medicine. [17] investigated the application of ensemble machine learning techniques to predict female infertility. Their study compared various ensemble methods, including Random Forests, Gradient Boosting Machines, and Voting Classifiers, to assess their effectiveness in predicting infertility based on patient data. The results demonstrated that ensemble methods consistently outperformed single models, underscoring the value of combining different classifiers to enhance predictive accuracy. This finding is particularly relevant in medical applications, where the complexity of patient data and the need for high accuracy necessitate robust modeling approaches. [18] conducted a comparative analysis of ensemble and single machine learning models to determine the most effective approach for predicting female infertility. Their study included models such as AdaBoost, Random Forests, and Gradient Boosting, and highlighted the superior performance of ensemble methods in capturing the intricate relationships between clinical risk factors and infertility outcomes. The integration of multiple ensemble learners not only improved predictive performance but also provided a more comprehensive understanding of the factors contributing to infertility, which is critical for developing effective treatment strategies. In another study, [19] focused on advancing Assisted Reproductive Technology (ART) through the implementation of an ensemble of heterogeneous incremental classifiers. Their model, which combined instance-based (IB1) learners and averaged one-dependence estimators (A1DEs), was designed to be updatable via a voting ensemble, allowing for continuous improvement as new data became available. The performance of this ensemble model was evaluated against other ensemble methods using ART datasets, demonstrating its efficacy in predicting infertility outcomes and supporting clinical decision-making processes. This study highlights the potential of ensemble learning to adapt to evolving medical data, thereby enhancing the applicability of predictive models in real-world clinical settings.

[20] explored the use of ensemble learning for the diagnosis of Polycystic Ovary Syndrome (PCOS), a condition closely associated with infertility. Their study involved a dataset of 117 women with 43 clinical characteristics and employed univariate feature selection and feature elimination techniques to identify the most relevant predictors of PCOS. The ensemble classifiers used in this study, including Voting Hard, Voting Soft, and CatBoost, were evaluated for their predictive accuracy, with Soft Voting achieving the highest accuracy at 91.12%. The identification and ranking of the top 13 most significant risk factors for PCOS provided valuable insights for early intervention and personalized treatment, demonstrating the utility of ensemble learning in managing infertility-related conditions. [21] designed an intelligent prediction model for female infertility using ensemble methods with biomarkers. Their study explored 26 variables, of which a subset was used as biomarkers for infertility prediction. By combining the strengths of Random Forest and J48 Decision Trees, the ensemble model achieved a significant improvement in predictive accuracy, with individual classifiers scoring 98.4% and 86.5% accuracy, respectively. The enhanced performance of the ensemble model underscored the importance of integrating multiple classifiers to achieve more reliable and accurate predictions, particularly in the context of complex medical conditions like infertility. In another approach, [22] developed an automatic ovarian tumor recognition system using an ensemble of convolutional neural networks (CNNs) combined with ultrasound imaging. The ensemble model was constructed from the outputs of ten CNN models, and its predictions were further refined using gradient-weighted class

activation mapping (Grad-CAM) technology to visualize decision-making results. The application of this ensemble approach to ovarian tumor prediction not only improved diagnostic accuracy but also provided clinicians with interpretable insights into the model's decision-making process, which is crucial for gaining trust in AI-driven medical tools. [27] applied advanced machine learning techniques, including both single models and ensemble learners, to predict female infertility. The classifiers explored in this study included Logistic Regression, Naive Bayes, Support Vector Machines (SVM), and a Random Forest ensemble learner. The Random Forest model was reported to outperform other classifiers, achieving an accuracy of 93%, which confirmed the utility of ensemble learning for early prediction of infertility and personalized treatment planning. This study emphasizes the importance of ensemble approaches in enhancing the accuracy and reliability of predictive models in clinical applications.

[28] utilised Random Forest classifier to determine infertility level in women. optimized features were explored with Particle Swam Optimization (PSO) classifier. The model built was an ensemble model called RF-PSO model. [29] implemented Neural Networks to develop a model known as Deep Inception -Residual Network model to predict personalized treatment for infertility couple before they started IVF procedure. Neural Networks were explored for the development of Deep Inception which predicted the infertility status of a couple before subscribed to treatment. The model was considered for couples that would undergo IVF procedures for their infertility. [30] employed six machine learning models, including Random Forest, Naive Bayes, Linear Regression, Decision Trees, AdaBoost, and k-Nearest Neighbors, to predict infertility in women and assess the success rate of In Vitro Fertilization (IVF). Among these models, the AdaBoost ensemble model demonstrated the highest accuracy at 97.5%, outperforming other classifiers and highlighting the effectiveness of ensemble techniques in complex predictive tasks related to reproductive health. [31] made comparative analysis between Support Vector Machine, Naïve Bayes Logistic Regression and Multi-Layer Perceptron classifiers to predict PCOS, one of the clinical risk factors of infertility. Muti-layer perceptron outperformed other classifiers. the study predicted PCOS, one clinical risk factor that inclined women to infertility. [32] also, evaluated the impact of sperm quality on infertility diagnosis and the success rate of clinical pregnancy using ensemble machine learning models. Their study utilized Random Forest as the primary ensemble method, which achieved the highest accuracy in predicting infertility for both men and women, as well as the likelihood of pregnancy success. The superior performance of the ensemble model in this context further supports the application of ensemble learning in reproductive health, where accurate predictions are essential for guiding treatment decisions and improving patient outcomes.

**Gap Analysis**

The application of ensemble machine learning techniques in predicting infertility has garnered significant attention in recent years, with numerous studies demonstrating their potential to improve diagnostic accuracy and support clinical decision-making. Despite these advancements, a critical gap remains in effectively addressing the specific challenges outlined in the problem statement, particularly concerning the predictive modeling of infertility in women within the context of Nigeria and similar regions. The problem statement highlights a drop in the fertility rate from 6.6 births per woman in 1973 to 5.1 births per woman in 2022, underscoring the urgent need for early and accurate prediction of infertility types to mitigate the emotional, psychological, and financial burdens faced by women and couples. While existing predictive models and ensemble techniques have made strides in this domain, they fall short in several key areas, failing to comprehensively address the nuanced and complex factors that contribute to infertility, particularly in diverse and underrepresented populations.

One of the primary limitations of the existing studies is the inadequacy of the datasets used. Many of the models developed in prior research, such as those by [16] and [20], are based on datasets that do not capture all relevant clinical risk factors associated with infertility. For instance, while these studies successfully utilized ensemble methods to predict treatment outcomes or specific conditions like PCOS, they did so with datasets that were either limited in scope or focused on specific subsets of the population, often excluding critical variables that are essential for a comprehensive understanding of infertility in a broader context. This limitation is particularly pertinent to the issue at hand, where the diversity of clinical risk factors—ranging from genetic predispositions to socio-environmental influences—is vast and poorly represented in the data. As a result, the models developed from these datasets may lack the depth necessary to provide human experts with the data-driven insights needed to make informed treatment decisions, especially in complex and varied clinical settings such as those found in Nigeria.

Furthermore, the problem of generalizability is a significant concern in the existing literature. Many studies, including those by [18] and [21], report high predictive accuracy within the confines of their specific datasets. However, these models often struggle to maintain their performance when applied to unseen data, particularly data that differs significantly from the training sets in terms of demographic and clinical characteristics. This issue of overfitting, where models are tailored too closely to the training data, limits the applicability of these models in real-world clinical settings where patient profiles can vary widely. In the context of the problem statement, this limitation is critical because it highlights a disconnect between the predictive models and the diverse populations they are intended to serve. The failure to generalize across different populations, particularly those underrepresented in training datasets, means that these models may not accurately capture the relationship patterns necessary for effective prediction and treatment of infertility in women, thereby limiting their utility in clinical practice.

Moreover, while the existing studies have demonstrated the potential of ensemble methods to outperform single models, there is still a gap in the strategic integration of these ensemble techniques to address the specific challenges of infertility prediction. For instance, the work by [19] on heterogeneous incremental classifiers offers an innovative approach to improving predictive accuracy over time as new data becomes available. However, this study and others like it often fail to address how these models can be effectively deployed in resource-constrained environments, such as those found in many parts of Nigeria. The implementation of such advanced ensemble methods requires not only robust computational infrastructure but also access to continuous streams of high-quality data, which may not be readily available in all clinical settings. This gap in practical applicability is a significant barrier to the adoption of ensemble models in real-world infertility prediction, particularly in regions where healthcare resources are limited, and the availability of comprehensive data is a challenge.

Additionally, there is a noticeable lack of focus on the integration of socio-cultural factors into the predictive models. The existing literature predominantly concentrates on clinical and biological variables, as seen in studies by [21] and [22], which emphasize biomarkers and imaging data, respectively. However, infertility is a multifaceted issue influenced not only by biological factors but also by socio-cultural and environmental determinants. In the context of Nigeria and similar regions, factors such as access to healthcare, cultural beliefs about fertility, and socioeconomic status play a crucial role in determining both the prevalence of infertility and the success of treatment interventions. The absence of these factors in the predictive models limits their relevance and effectiveness in addressing the overarching issue of infertility in women as highlighted in the problem statement. Without a holistic approach that incorporates these socio-cultural dimensions, the predictive models may offer limited insights and fail to resonate with the lived experiences of the women they are intended to help.

The reliance on static datasets in the existing literature also represents a critical gap. Infertility, particularly in the context of ART, is a dynamic condition where treatment outcomes can evolve over time based on ongoing interventions and changes in patient health status. However, most of the studies reviewed, including those by [17] and [30], rely on static snapshots of patient data to build their models, which may not fully capture the temporal aspects of infertility. This static approach limits the ability of the models to adapt to new information or changes in patient profiles, reducing their effectiveness in ongoing clinical decision-making. The development of predictive models that can incorporate temporal data and adjust predictions based on longitudinal patient information is an area that remains underexplored but is crucial for advancing the field of infertility prediction.

Finally, while the problem statement calls for a model that harnesses the predictive accuracy of multiple classifiers, the existing literature does not adequately address the challenges associated with model interpretability. Ensemble models, by their nature, can be complex and difficult to interpret, which poses a challenge for their adoption in clinical settings where transparency and explainability are paramount. Clinicians and healthcare providers need to understand the rationale behind model predictions to make informed decisions and communicate these effectively to patients. Studies like those by [32], which focus on the technical performance of ensemble models, often overlook the importance of interpretability, thereby limiting the practical utility of these models in clinical practice. Addressing this gap requires the development of ensemble models that not only deliver high predictive accuracy but also offer clear and interpretable insights that can be easily understood and applied by healthcare professionals.

Thus, while the existing body of work on ensemble machine learning for predicting infertility in women has made significant contributions to the field, there are substantial gaps that need to be addressed to fully meet the challenges outlined in the problem statement. These include the need for more comprehensive and diverse datasets, improved generalizability of models to diverse populations, practical considerations for deployment in resource-limited settings, integration of socio-cultural factors, dynamic modeling approaches, and enhanced model interpretability. Addressing these gaps is essential for developing robust, accurate, and applicable predictive models that can truly advance the field of infertility prediction and support effective treatment decisions in diverse clinical contexts.

## Methodology

This section focused on the implementation tools and how they might be used to construct the proposed model. Also, how the dataset was preprocessed, the methods employed for training the model and characteristics of the dataset were discussed. The section finished with detailed descriptions of the recommended metrics for evaluating the proposed model. The model would compensate for the deficiencies in objectivity and health centric procedures needed in prediction of women infertility by filling the gaps acknowledged in existing works. An ensemble model was developed by harnessing the predictive power of two distinct machine learning models eXtreme Gradient Boosting (XGBoost), Extremely Randomized Trees (Extra Trees) and one deep learning model known as Convolutional Neural Networks (CNNs). These base models were stacked with Random Forest as the meta-model. The clinical risk factors that inclined women to infertility was used to train the base models. Feature selection was carried out to acknowledge the most significant features for the prediction.

**Dataset**

The clinical risk factors for the proposed research were Amenorrhea, Asherman's syndrome, cervical factor, congenital factors, endometriosis, fibroids, fluid in endometrium, hysteroscope, hormonal factors, hormonal imbalance, low ovarian reserve, pelvic adhesion, pelvic inflammatory, perforation in uterus, poor ovarian reserve, polycystic ovary, prolactinoma, tubal blockage, tubal factors, low ovarian reserve, menopause and uterine fibroids with the respective demographic records [33 - 36]. They were the factors available in the 5,000-dataset collected from mother & Child and Havilard hospitals in Nigeria. The dataset considered women between age 25 to 55 years. These hospitals have branches in centralized places across Nigeria and update medical records of over two decades for infertility women.

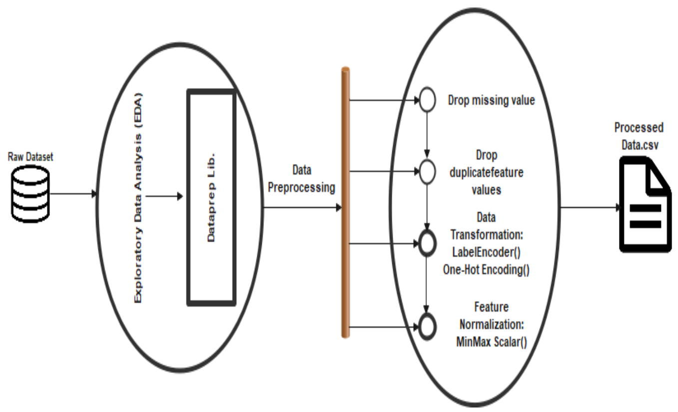



Figure 1: Data Processing and Data Transformation

The processed data is further preprocessed to transform the categorical feature labels of the dataset. The dataset contains 26 feature labels of one of these feature labels is known as the target label. The target label is what this study seeks to predict. The target label is labelled "Infertility type" which has two possible values (1st Degree Fertility and 2nd Degree Fertility). The preprocessed dataset will be transformed into numerical representations for further preprocessing. Thereafter, feature selection is done using Random Forest/Recursive Feature Elimination (RF/RFE) method.

**Feature Elimination/ Feature Selection**

This study proposes to use the Random Forest/Recursive Feature Elimination (RF/RFE) method because it has the benefit of considering the relevance, redundancy, and interactions amongst all the features in the dataset. RF/RFE will successfully decrease the dimensionality of the dataset while keeping the most useful features by deleting the least important characteristics iteratively. The RF/RFE model as shown in Figure 3.2, will receive the preprocessed data and selects good number of quality features that characterize the factors that help to predict infertility types.

Random Forest: Random Forest is an ensemble machine learning algorithm that would be used to rank the importance of the features in the processed dataset. It gives each feature a relevance value depending on how much it adds to the model's ability to produce correct predictions. The significance score is computed by calculating the decrease in impurity when a certain characteristic is applied to separate data at a tree node. Features with higher significance ratings are more relevant in creating predictions and are chosen for feature selection. This will be used to rank and choose the most significant characteristics, lowering the dataset's dimensionality while maintaining the most useful features.

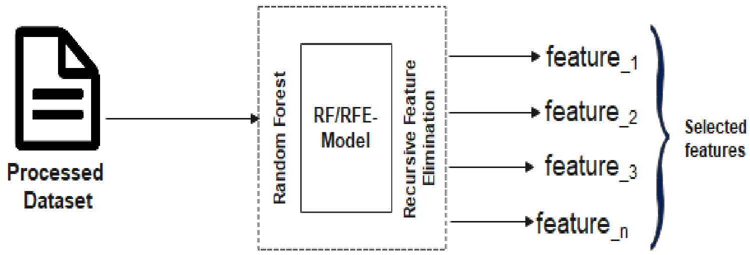



Figure 2: Feature Selection Using RF/RFE model.

Recursive Feature Selection: The RFE will use the Random Forest (RF) to recursively eliminate the least important features from the dataset. It will iteratively remove the least important feature(s) until a specified number of features remains. This study adopted the use of feature reduction because the dataset has much data features. Also, it is based on the idea that by removing less important features, a model's performance will not significantly degrade but can achieve better model generalization [37]. This study will specify the desired number of features to be selected, then the RFE automatically eliminates the rest. These number of selected features are seen as feature_1, feature_2, feature_3 and so on. Where feature_n represents the last number of features. After the feature selection, the datasets will be used to train the proposed Ensemble Deep Learning Model.

**Model Building**

The model will be built using two traditional machine learning algorithms (XGBoost and Extra Trees Classifier), and one deep learning algorithm (CNN). These algorithms will be trained using the processed dataset with all the data features and with the selected features. This will be done to ascertain the efficacy of the feature selection. If the model of all the features dataset outperforms the model of the selected features dataset, then the study will consider the feature selection model unnecessary. Otherwise, we will use the selected features model. The performance of (XGBoost, Extra Trees Classifier, and CNN) models will be evaluated based on their individual ability to predict correctly the infertility types. Figures 3.3 and 3.4 shows a detailed description of the model design. Figure 3.3 shows a typical single model, which represents individual machine learning algorithm that would be used in this study. Figure 3.4 shows the combination of the strength of the three models. The three models are combined to develop the ensemble model using staked ensemble method.

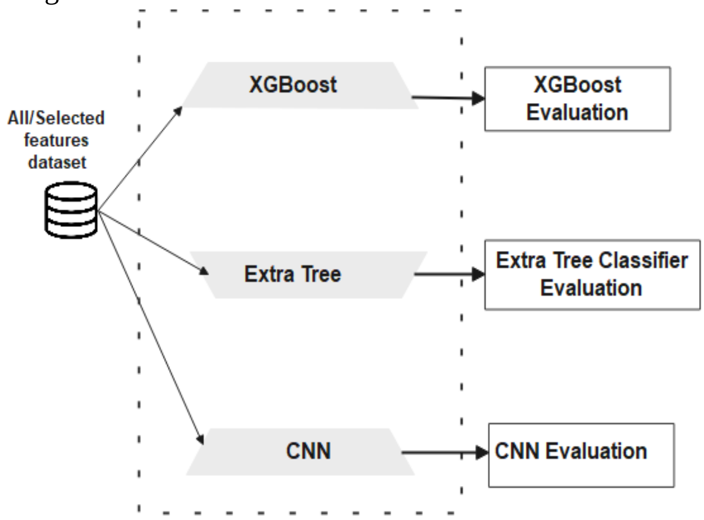



Figure 3: XGBoost, Extra Tree and CNN Individual Model

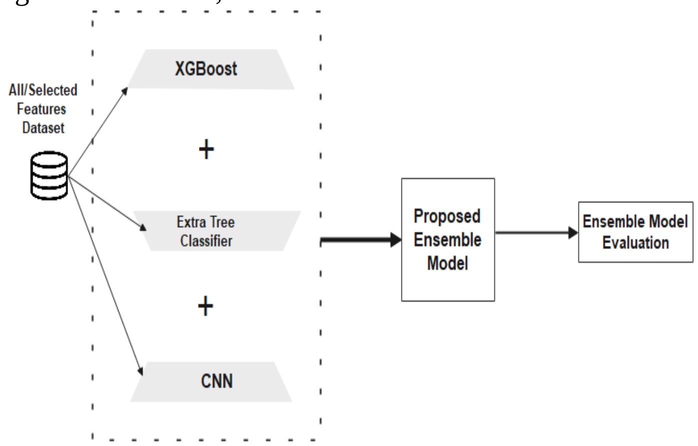



Figure 4: Combination of the Three Models

The three base models (Decision Tree, XGBoost, and a CNN) would be trained. Each model will make predictions on the training data. The prediction from each base model becomes new features for a meta-model. A final model (the stack ensemble model) was trained on the combined features.

**Mathematical Representations of the Base Models**

**XGBoost**

XGBoost is an ensemble learning algorithm that utilizes the gradient boosting framework. XGBoost combines decision trees as base learners with regularization techniques, known for computational efficiency, efficient data handling, insightful feature importance analysis, and handling of missing values. This algorithm, applicable to various tasks such as regression, classification, and ranking, is widely used. Its objective function is given in equation (1).

$$P(y = k \mid x) = \frac{e^{w_k^T X}}{\sum_{j=1}^{K} e^{w_j^T X}} \text{----------------------------------(1)}$$

where $w_k$ are the weights for class $k$, $K$ is the total number of classes, and $X$ is the input feature vector.

The number of boosting rounds, that is, the number of trees in the ensemble is given in equation 2.

$$\hat{y} = \sum_{m=1}^{100} \alpha_m \, h_m \, (x) \text{ ----------------------------------(2)}$$

where $h_m$ are the individual trees and $\alpha_m$ are their respective weights.

The learning rate, which the step size shrinkage used in the update to prevent overfitting is given in equation (3).

$$w_{t+1} = w_t - \eta \boldsymbol{\nabla L} \, (w_t) \text{ ----------------------(3)}$$

where η is the learning rate (0.3 will be used in this study).

A regularization term will be added to the weight using the equation (4).

$$Regularization\ Term = 0.1 \sum_{j=1}^{p} |w_j| \text{------------(4)}$$

**Extra Tree Model**

The Extra Trees algorithm creates numerous decision trees, each with unique random samplings. The modified equation that will be adopted is given in equation (5). The identifies the number of trees in the forest.

$$\hat{y} = \frac{1}{100} \sum_{m=1}^{100} h_m \, (x) \text{ ----------------------------------(5)}$$

where $h_m$ are the individual decision trees.

The criterion function will be set to ‘gini’ as given in equation (6).

$$G = \sum_{i=1}^{C} p_i (1 - p_i) \text{ -------------------------------------(6)}$$

where $p_i$ is the probability of class $i$ and $C$ is the number of classes.

The maximum feature is given in the equation 3.8, where the square root of the total number of features is taken.

$$max\_features = \sqrt{p} \text{ ----------------------------------(7)}$$

where $p$ is the total number of features.

### Convolutional Neural Network

The Convolutional Neural Network (CNN) model using the Sequential API from Keras. The model architecture will consist of a 1D convolutional layer, followed by a flattening layer, a dense (fully connected) hidden layer, and an output layer. The detailed description and the mathematical representation of the key components are shown in the following equations. Equation (8) represents the relationship between the activation function and the filter weight and size.

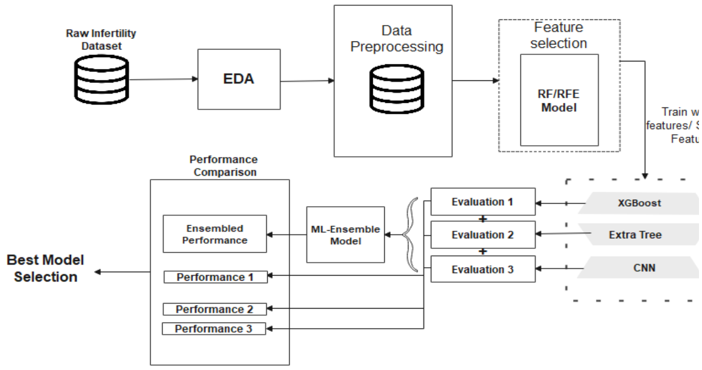
$$Conv1D(x,w) = ReLU(\sum_{i=1}^{3} x_{t+i-1}.\ w_i + b) \text{ --------(8)}$$

where $x$ is the input sequence, $w$ is the filter weights, and $b$ is the bias term.

### General Model for Predicting Types of Infertility in Women using the dataset of Clinical factors that inclined women to infertility

The general model includes the data preparation step as well as the model building stage. This will be accomplished by creating a workflow that begins with data preliminary treatment and progresses to the completion of model entities.

Figure 5 depicts the proposed system's framework.




### Conclusion

Thus, this study addresses a critical gap in the predictive modeling of infertility in women, particularly within the context of Nigeria and similar regions. The development of a stacked ensemble machine learning model, which combines eXtreme Gradient Boosting (XGBoost), Extremely Randomized Trees (Extra Trees), and Convolutional Neural Networks (CNNs), represents a significant advancement in the field. This model harnesses the predictive power of multiple classifiers to improve accuracy, robustness, and generalizability, offering a more comprehensive tool for infertility prediction.

The proposed model's ability to capture complex relationships among clinical risk factors and its potential to provide early and accurate diagnoses is pivotal in supporting personalized treatment plans in Assisted Reproductive Technology (ART). This approach not only enhances decision-making processes for human experts but also mitigates the emotional, psychological, and financial burdens faced by women and couples dealing with infertility.

While existing studies have demonstrated the effectiveness of ensemble methods in medical predictive modeling, this research builds on their foundations by addressing specific limitations such as the inadequacy of datasets, generalizability issues, and the lack of socio-cultural considerations. The integration of a more diverse and representative dataset, combined with advanced machine learning techniques, ensures that the developed model is both interpretable and applicable in real-world clinical settings.

Furthermore, the strategic deployment of the ensemble model in resource-constrained environments underscores its practical utility in regions with limited healthcare infrastructure. By bridging the gap between theoretical models and practical application, this research contributes to the broader goal of improving reproductive health outcomes and advancing the field of infertility treatment.

Future work should focus on refining the model's adaptability to evolving clinical data and enhancing its interpretability for seamless integration into clinical workflows. By continuing to explore the intersection of machine learning and reproductive medicine, there is potential to further improve the accuracy and effectiveness of infertility predictions, ultimately leading to better patient outcomes and a deeper understanding of the factors influencing infertility.

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