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An Ensemble Machine Learning Approach for Pre-IVF Prediction of Live Birth Outcomes

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Abstract

This study aims to develop an AI driven model to predict in vitro fertilization (IVF) outcomes and improve the cost effectiveness of reproductive treatments. The primary objective is to estimate the likelihood of a live birth from the outset using advanced data processing techniques. Prediction models were applied to forecast live births among women undergoing their first cycle of fresh or frozen IVF or intracytoplasmic sperm injection (ICSI), incorporating both pre cycle and post cycle factors. A key focus of this work is predicting live birth probability when embryos originate from a couple rather than a donor. Using the publicly accessible Human Fertilization and Embryology Authority (HFEA) dataset, we evaluated several AI approaches, including Random Forest, Gradient Boosting, and a proposed ensemble machine learning algorithm. Data were preprocessed using the Auto Label Encoder technique. Model performance was assessed through confusion matrices, F1 scores, precision, recall, and receiver operating characteristic (ROC) curves. The ensemble algorithm achieved the strongest overall performance, with accuracy of 79, precision of 77, recall of 76, and an F1 score of 76.49. Gradient Boosting demonstrated the highest recall (80.48) but showed average performance in other metrics. Random Forest yielded comparatively lower accuracy and F1 scores, indicating limitations in class differentiation. These findings suggest that ensemble based AI models offer a more robust approach for predicting live birth outcomes in IVF treatment pathways.

Keywords: Livebirth prediction, Human Fertilization and Embryology Authority, Random Forest, Auto Label Encoder, Gradient Boosting, Ensemble machine learning algorithm

Introduction

Failure to conceive after six months of constant and unprotected sexual intercourse is called infertility and has been identified as a leading global health issue over the years. The rate of infertility is quite high in the couples all around the world, and in most cases, it causes mental imbalances, societal stress and economic strain. In order to out of this state, assisted reproductive technologies (ART), specifically in vitro fertilization (IVF) have become very common. IVF refers to a medical technique whereby fertilization of the oocyte is carried out outside of the human body under regulated laboratory conditions and that fertilized embryo is inserted into the uterus in order to be pregnant. In other instances, ICSI is employed to inject a single sperm directly into the oocyte in order to increase fertilization success. Despite the revolution that is IVF in reproductive medicine, the success rate of live birth is still questionable and is associated with various patient and clinical factors.IVF procedure comprises of the following stages; ovarian stimulation, egg retrieval, fertilization, embryo culture, and embryo transfer. The products of each of the stages are valuable clinical and embryological data that can be used in predictive analysis. But the IVF treatment has some medical and psychological risks. Research has found links between IVF and perinatal affective disorders (Capuzzi et al., 2020) or pregnancy-related issues, including preeclampsia (Gui et al., 2020).

Moreover, the emotional state can be affected by stress encountered in the course of treatment, and this aspect can potentially affect the treatment outcome (Koumparou et al., 2021). These aspects emphasize the need to have precise early prediction models which can be used in clinical decision making and minimization of unnecessary treatment cycles. The current trends of artificial intelligence (AI) and deep learning have offered powerful means of outcome prediction within the field of reproductive medicine. Embryo datasets in large scale have been already analysed with deep learning techniques to effectively predict live birth outcomes with promising accuracy (Huang et al., 2022).

Moreover, studies of the comparison between assisted fertilization in animal models have confirmed the extended consequences of reproductive technologies on the traits of fertility and long-term outcomes (Lafontaine et al., 2023). Regardless of such developments, most of the existing models have limitations that include decreased generalizability, less emphasis on first-cycle prediction, and a lack of emphasis on cost-effectiveness. Hence, this paper hypothesizes an AI-based ensemble machine learning algorithm to forecast the chance of a live birth in the first IVF/ICSI cycle with publicly accessible HFEA data. The proposed framework incorporates effective preprocessing in the form of Auto Label Encoding and comparisons between multiple classifiers (Random Forest and Gradient Boosting) to enhance the performance of prediction and assist the economical and data-oriented use of prediction to make decisions in reproductive treatments. The primary goal of the work is as follows.

- Designing a prediction model based on Artificial Intelligence for estimating the risk of achieving a live birth at the start of the IVF or ICSI treatment cycle. The first step will begin with Data Cleaning of the HFEA dataset followed by Auto Label Encoding as the model input requires appropriate pre-processing and formatting.
- To analyse and compare different machine learning algorithms on the basis of metrics like Accuracy, Precision, Recall, F1-score, ROC-AUC, and Confusion Matrices, notably Random Forest, Gradient Boosting, Logistic Regression, and XGBoost.
- To determine the model that would be the most clinically useful and economically productive, that could subsequently assist physicians and couples in making informed decisions prior to IVF/ICSI therapy.
- To explore the effect of pre-cycle and post-cycle parameters on the odds of live birth. In particular, to focus on the cycles that involve the use of the couple’s own embryos as opposed to those that use donated embryos.

There are four primary phases in the model creation process. Step 1 involves gathering literature work, which is a compilation of different kind of dataset and machine learning model. Step 2: Pre-process the dataset using certain methods to choose features, normalize the data, and standardize the format. Step 3: Use different machine learning methods to train prediction models. Step 4: Assess each model's performance to choose the best one.

Literature Review

Louis et al. (2021) reviewed the application of deep learning–based computer vision (DL-CV) in IVF and paid strong attention to the use of convolutional neural networks (CNNs) to carry out automated embryo evaluation and grading. The review acknowledged the potential of AI-based image analysis to enhance the accuracy of embryo selection and limit subjectivity in clinical decision-making, but also noted the lack of standardized datasets and adequate external validation. Luke et al. (2020) examined the relationship between IVF treatment parameters and hypertensive disorders of pregnancy in a population-based cohort analytical study and found a significant association, but could not establish causality due to the observational study design. Nagy et al. (2020) suggested vitrification technology (VT) as a fast-freezing technique to ensure higher embryo survival and safety rates than standard freezing; however, they also mentioned a complicated technical structure and financial demands as common disadvantages.

Peipert et al. (2022) assessed the effect of Comprehensive State Insurance Mandates (CSIM) on IVF and embryo transfer practices and outcomes through comparative statistical models and found better access to treatment but less available long-term follow-up analysis. Artificial Intelligence–Assisted Reproductive Technology Live Birth Prediction Models (ART-LBPM) were developed by Peng et al. (2024) on the basis of machine learning algorithms, including Random Forest (RF) and Gradient Boosting (GB). These models proved to be more predictive, although challenges regarding model interpretability and overfitting were also observed. The systematic review and meta-analysis by Pinborg et al. (2013) aimed to investigate adverse perinatal outcomes in ART-conceived singletons and found that the risks were high; yet, the presence of confounding factors related to the parents and their infertility prevented a clear conclusion.

Salmanian et al. (2020) performed a multivariate regression analysis to determine whether IVF is an independent risk factor for placenta accreta spectrum, but heterogeneity of the sample and lack of generalizability were noted as limitations. Sanderman et al. (2022) conducted a systematic review of the literature and analysed female dietary habits and IVF outcomes, suggesting that they might have a nutritional impact; however, comparison across studies was limited due to inconsistent measurement of dietary practices. Shingshetty et al. (2024) used multivariable predictive regression to identify factors that predict IVF success, but diversity in clinical populations reduced predictive robustness.

The initial successful birth following embryo reimplantation, reported by Steptoe et al. (1978), formed the basis of the contemporary practice of IVF; however, these initial procedures had low success rates and were limited by technological constraints. The Single Embryo Transfer (SET) strategy suggested by Tiitinen (2019) to minimize multiple pregnancies is based on selecting embryos with the highest developmental potential, yet accurate embryo selection is difficult without highly predictive systems. Von Schondorf-Gleiker et al. (2022) reconsidered ethical aspects in IVF using an Ethical Framework Analysis (EFA), which highlighted issues of embryo selection and fair access, although ethical considerations vary worldwide.

A risk-of-pregnancy and multiple-pregnancy prediction tool called the Artificial Intelligence Prediction Model (AIPM) was proposed by Wen et al. (2022) as a predictor of pregnancy and multiple-pregnancy risk after IVF–Embryo Transfer (IVF-ET). The model showed promising predictive results but required additional external validation. Wessel et al. (2023) examined Alternatives to In Vitro Fertilization (A-IVF) by comparing them to clinical analysis, but the success was highly dependent on the cause of infertility in the patient. Zhang et al. (2022) created a Machine Learning-Based Live Birth Prediction Model (ML-LBPM) and trained it with large-scale natural-cycle IVF data, which demonstrated high predictive accuracy; however, they acknowledged that retrospective data were biased and not all variables were considered. Lastly, using biochemical correlation modelling, Zhou et al. (2021) investigated the relationship between exposure to metal elements and IVF outcomes, but environmental heterogeneity and the small sample size limited generalizability.

Methodology

Making an AI model to predict live birth results of various treatments (IVF, ICSI, etc.) starts by isolating birth data from the larger dataset. The dataset contains all relevant details about the patient, and the treatments (clinical steps). Knowing the patient and treatments, and understanding the outcomes, we can see the overall pattern. Input then goes through an Auto Label Encoder to transform all categorical variables into numbers (machine learning). Four algorithms will intersect the data and look for the 'successful live birth' outcomes. Training occurs through the processed dataset. The algorithms to use are, Linear Regression, Random Forest, Gradient Boosting, and XGBoost.

They will all get the opportunity to get the data and test the success of their predictions. Once trained, each algorithms performance will be measured through distinct values (Key performance indicators, or KPIs). The model's success can be measured through, accuracy, precision, recall, F1, and AUC-ROC. The KPIs ascertain the model's success in classifying positive results, distinguishing the successful from the unsuccessful cycles. Then the best model can be picked. This will be the best and most valid predictive model. The pipeline assists in finding the one with the strongest model confidence values. This data will increase the success of IVF treatments and improve overall predictions.

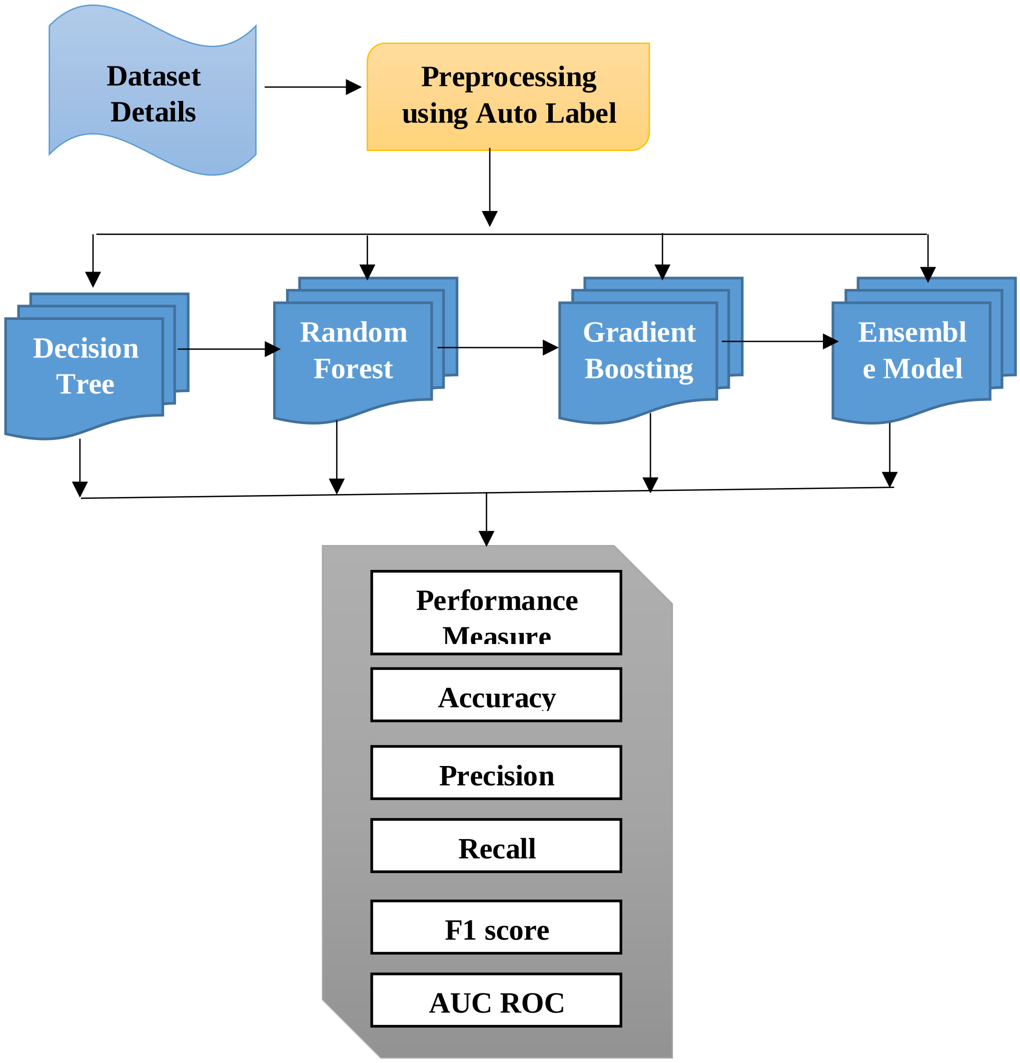

Figure 1. Overall architecture diagram of proposed work

Dataset Details

The HFEA, which gathered information and statistics about the reproductive treatment cycles carried out annually in the UK, provided the dataset. In order to enhance patient care and assist researchers in conducting top-notch research while guaranteeing extremely high patient, donor, and offspring anonymity, HFEA maintains the world's longest-running registry of fertility treatment data. 760,732 cycle records with 95 fields on treatment cycles initiated between 2005 and 2016 made up the study's raw dataset. Since the primary goal of this study was to predict the incidence of live births, the "Live birth occurrence" field was considered the prediction label, while the remaining 94 fields were considered characteristics. In a single cycle, each record reflected the circumstances of the patients.

In a single cycle, each record reflected the circumstances of the patients. Couples having IVF, including intracytoplasmic sperm injection (ICSI), were first taken into consideration.

"Egg donation," "Sperm donation," "Embryo donation," and "Surrogate" were not included. Second, "Stimulation used" in the raw dataset refers to the use of exogenous gonadotropins in IVF to promote the development of several eggs simultaneously (7, 29, 30). Therefore, patients undergoing NC-IVF who had no "stimulation used" were taken into account in this study. The subsequent frozen-thawed cycles from NC-IVF were then added, along with fresh cycles. Cycles with finished ET were also provided. Ultimately, 57,558 cycle records—that is, 57,558 NC-IVF cycles were kept for additional study after certain records containing outliers like "999" were removed. 94 characteristics are present in the raw dataset. Clearly, not every trait had a major impact on the likelihood of a live delivery. Features pertaining to "Egg retrieval," "Egg stored," "Fertilization," "Embryo transfer," and "Embryo stored" were eliminated since our prediction model was created as a pretreatment model to forecast the couple's live-birth occurrence before to the initiation of IVF therapy. Conversely, characteristics pertaining to "patient age," "couple's prior pregnancy status," "pregnancy-related treatments," "type of infertility," "cause of infertility," "treatment type," "fresh cycle," and "frozen cycle" were included (Zhang Yanran et al., 2022).

Data Pre-processing

Automatic Label Encoding This is an automatic data preparation step where all the categorical columns in a dataset are transformed into numerical labels without an operator given. This is useful machine learning model does not work with text values are transformed. Label Encoder detects string/object columns and converts them into numerical codes. This approach works best in automatically data scanning where the dataset is examined and columns with characters are detected (for example, Male, Female, Yes, No, Fresh Cycle, and so on) then the Label Encoder is applied to all of them. It makes the pre-processing pipeline in a fast and uniform manner, highly scalable to large size datasets like HFEA IVF data. The label encoding converts each unique categorical value into a numeric ID. For a categorical column C with unique values.

$$C = \{v1, v2, v3, \ldots.., vn\} \qquad (1)$$

Label encoding assigns: Encoded

$$\text{Encoded (vi)} = \text{I} - 1 \qquad (2)$$

Advanced Machine Learning model for live birth prediction

Random Forest

By combining the predictions of several decision trees, Random Forest is an ensemble learning technique that enhances classification performance. When compared to a single decision tree, this method lowers variance and overfitting. Each tree is trained on a random subset of the data, chosen with replacement, using bagging (Bootstrap Aggregating). By merely taking into account a random subset of characteristics at each split, the trees are further varied and the correlation between them is lessened. The number of trees in the forest is determined by the n_estimators argument; more trees often result in better performance but longer calculation times. Each tree's depth is limited by the max_depth option; deeper trees may overfit but capture more intricate patterns. The amount of features taken into account for splitting at each node is determined by the max_features parameter, which has a standard value of "sqrt" (the square root of the total number of features). The criteria parameter gauges the split's quality; "gini" and "entropy" are frequently employed, with Gini impurity being a little quicker. The minimal number of samples needed to divide a node is specified by the min_samples_split option; larger values may lessen model complexity but assist avoid overfitting. The minimum number of samples needed to be at a leaf node is also set by min_samples_leaf, which starts at 1 and is modified based on the data. Because several trees are averaged, Random Forests are also resistant to overfitting and may use surrogate splits to address missing data. Furthermore, Random Forest features an integrated feature selection method that finds the most important variables and offers insightful information about how they affect the model's predictions.

Gradient Boosting Algorithm

Gradient Boosting is an ensemble learning method in which models are constructed one after the other, with each new model attempting to fix the mistakes of its predecessors. The architecture diagram shown in figure 2, the detailed pipeline of gradient boosting algorithm. The Random Forest algorithm is base line of the gradient boosting algorithm. The architecture begins with base model as random forest algorithm, its prediction function in equation (3),

$$f(x) = \arg\min \sum_{i=1}^{n} L(y_i\,, \gamma) \tag{3}$$

n case of regression, this is usually equal to the mean of the target variable. In every iteration m, gradient boosting works out the pseudo-residuals, the negative derivatives of the loss function with reference to the predictions of the existing model:

$$\gamma_{im} = -\left[\frac{\partial L\big(y_i,\ f(x_i)\big)}{\partial f\big(f(x_i)\big)}\right]_{f(x)=f_{m-1(x)}} \tag{4}$$

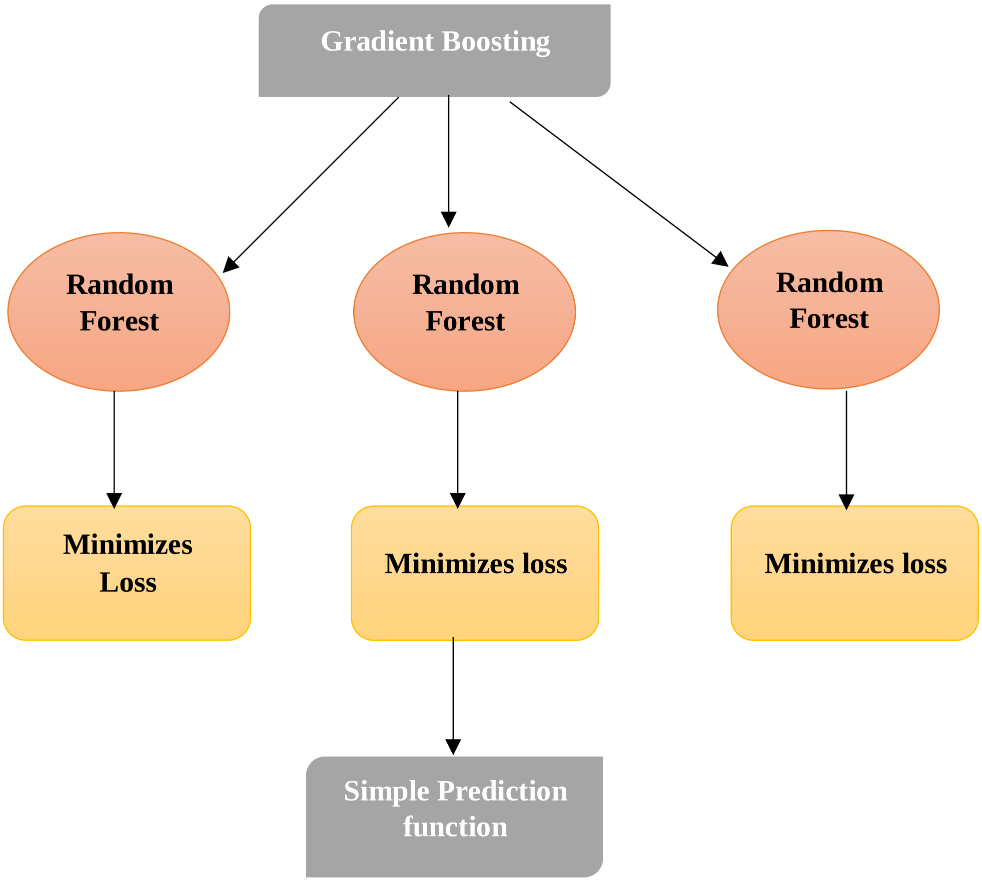

Figure 2. Flow diagram of Gradient boosting algorithm with Random forest algorithm

The small decision tree h(x) is trained to predict these residual

$$h(x) = r_{im} \tag{5}$$

The trees aim at reducing loss by fitting the errors of the other trees. This comes out in the architecture whereby all blocks of the Decision Tree leads to Minimizes Loss. Moving in m steps the resulting f m (x) final function is a good predictor, an amalgamation of weak learners derived in equation (6).

$$f_m\ (x) = \ F_0(x) + \sum_{m=1}^{M} n\, \gamma_{im}\ h(x) \tag{6}$$

Ensemble Machine learning model

The architecture diagram in figure 3, is a composite ensemble model that is an integration of the predictive capabilities of the Random Forest and gradient boosting to enhance the overall model performance. The input data is processed in real time, and it is directed into two learning models that process data independently. The initial one effectively implements a Random Forest algorithm, whereby several decision trees are trained with bagging and randomness of features to generate a prediction function that remains consistent f (x).

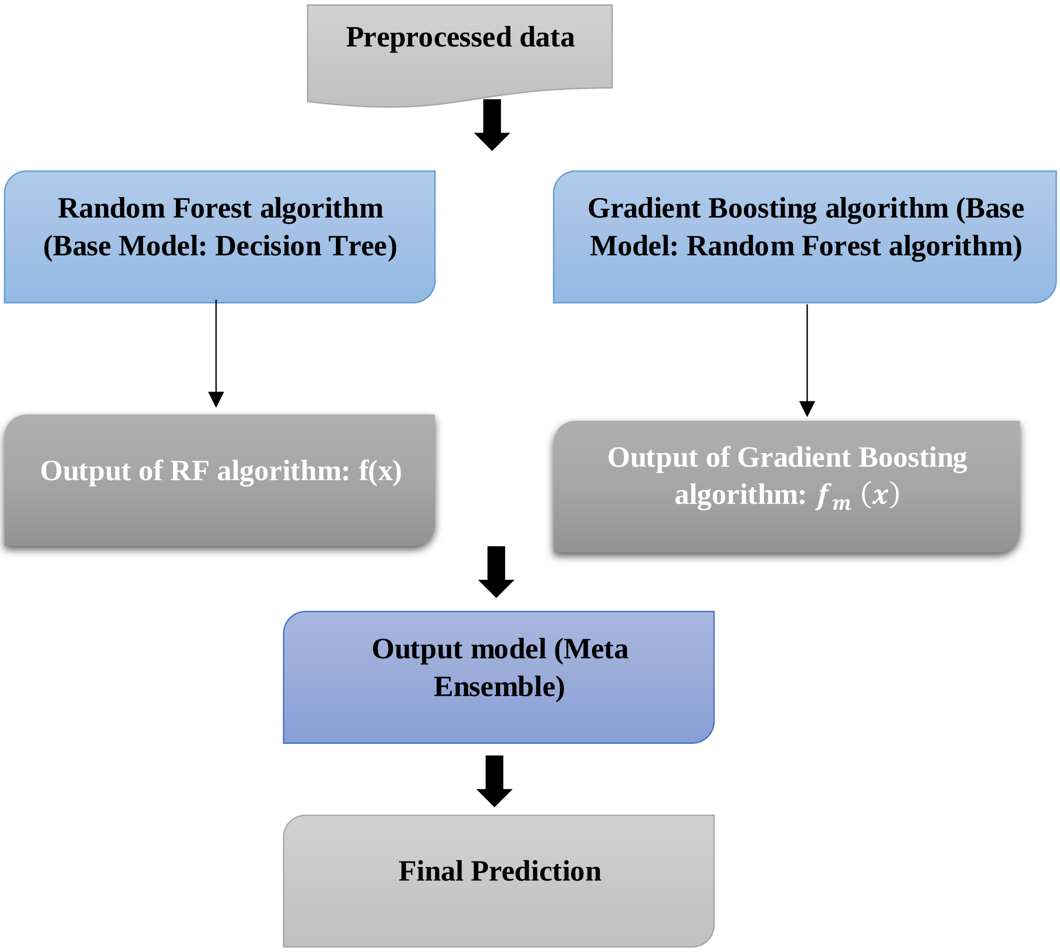

Figure 3. Proposed Ensemble Machine Learning model's architecture diagram

The second branch uses a Gradient Boosting algorithm, which trains models one after another, with a random forest base learner being the initial one, to minimize the residual errors in each iteration to produce the boosted prediction output. These two outputs are then combined in a meta-ensemble layer, the prediction probability of these two outputs is then combined either by averaging, weighted fusion or stacking using a meta-learner. The combination of the two models is the complementary behaviour of both the Random Forest variance reduction and Gradient Boosting bias reduction which provide a stronger and more accurate final prediction. This mixture method can increase the generalization, stability and reliability and is therefore very useful in complicated tasks like medical outcome forecasting and IVF live birth forecasting.

Results and Discussion

This study uses scikit-learn for ML classifiers and the TensorFlow library with a Keras backend for deep learning classifier training. F1-score, precision, recall, ROC AUC scores, and curves comparing different models are the metrics that are compared in this study. The outcomes of trained model such as Random Forest algorithm, Gradient boosting and ensemble learning model shown in this section. Few of the 94 variables in the raw dataset had a substantial impact on predicting the occurrence of live births. The properties of the sperm and egg sources, as well as the stimulation employed, determine how the dataset is filtered. Patient data are taken into consideration if the sperm and egg originate from the same couple, i.e., Partner and Patient; all other records are discarded. In IVF, females are administered with a drug that contains both luteinizing hormone (LH) and follicle-stimulating hormone (FSH) to encourage the development of several eggs at once45. The dataset refers to it as "Stimulation Used"; this study solely takes into account patient records in which stimulation is performed. Few patient records had the value 999 in the field "Patient Age at Treatment," which are removed. Age ranges and text are transformed into categorical data.

The goal variable, "Live-birth Occurrence," is a numerical field with values between 0 and 5, where 0 denotes no birth (negative class) and higher than 1 denotes birth occurrence (positive class). All patient records with Live-birth Occurrences greater than 1 are set to 1 and the remaining records to 0 in order to create a binary categorization. The Table 1 shows the performance comparison of different machine learning algorithm.

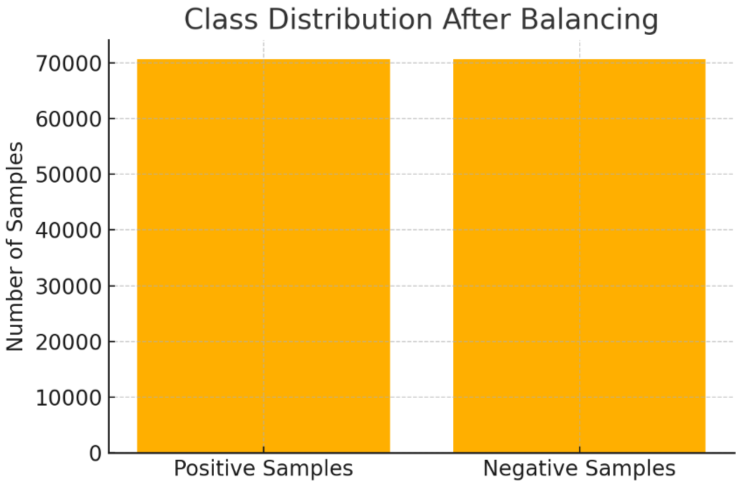

Figure 4. Balanced Dataset (data balance depends on target variable)

Table 1. Performance Comparison of proposed model with conventional ML model

Algorithm	Accuracy	Precision	Recall	F1 score value	AUC-ROC
Random Forest algorithm	73.2	73	72	72.49	0.78
Gradient Boosting algorithm	75.4	74	72	80.98	0.77
Ensemble machine learning algorithm	79	77	76	76.49	0.89

The performance comparison demonstrates that ensemble machine learning model has better results than the individual random forest algorithm and the gradient boosting algorithm in all evaluation measures. The accuracy of the Random Forest model is 73.2 with a precision of 73, a recall of 72, an F1-score of 72.49, and an AUC-ROC of 78.00, which is the moderate prediction capacity. Gradient Boosting is a little more accurate, with an accuracy of 75.4, and minor increases in its precision, recall, and F1-score, which is good in decreasing bias with sequential learning. Nonetheless, the highest accuracy of 79% is obtained by the ensemble model, which is formed by the combination of the results of the two algorithms, and its accuracy is better (77%), recall (76%), and F1-score (76.49%). Most importantly, it has a significantly higher value of AUC-ROC of 84.90, which is more discriminating between positive and negative classes. This enhancement confirms that the hybrid ensemble is working as expected wherein the complementary strengths of the two base models are well utilized to form a more robust and reliably predictive system.

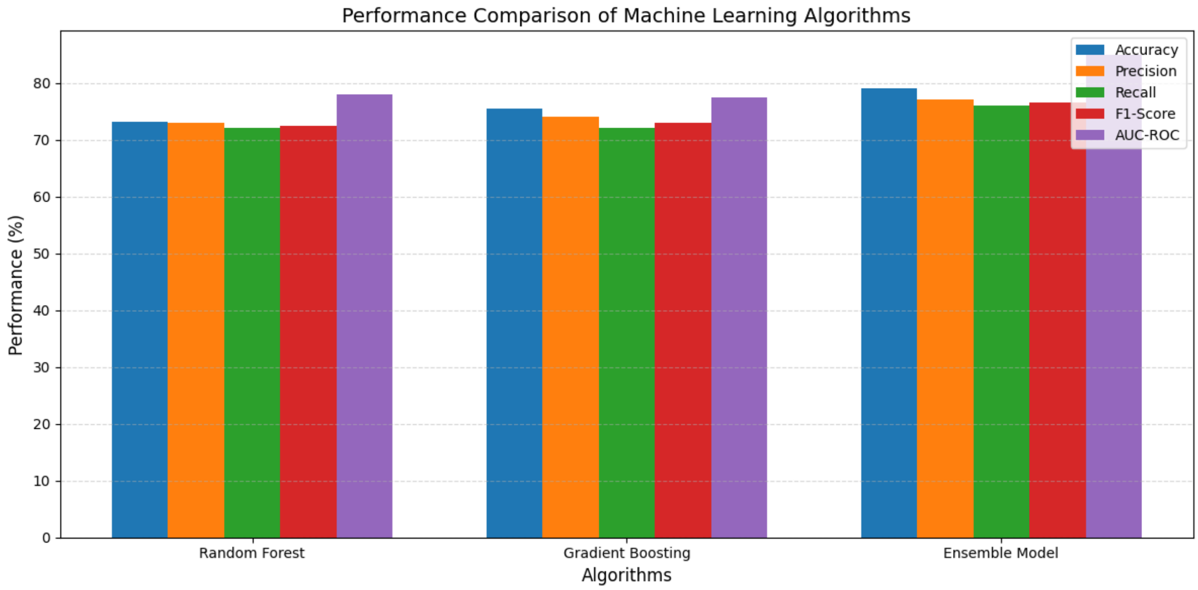

Figure 5. Performance comparison of conventional machine learning model with proposed model

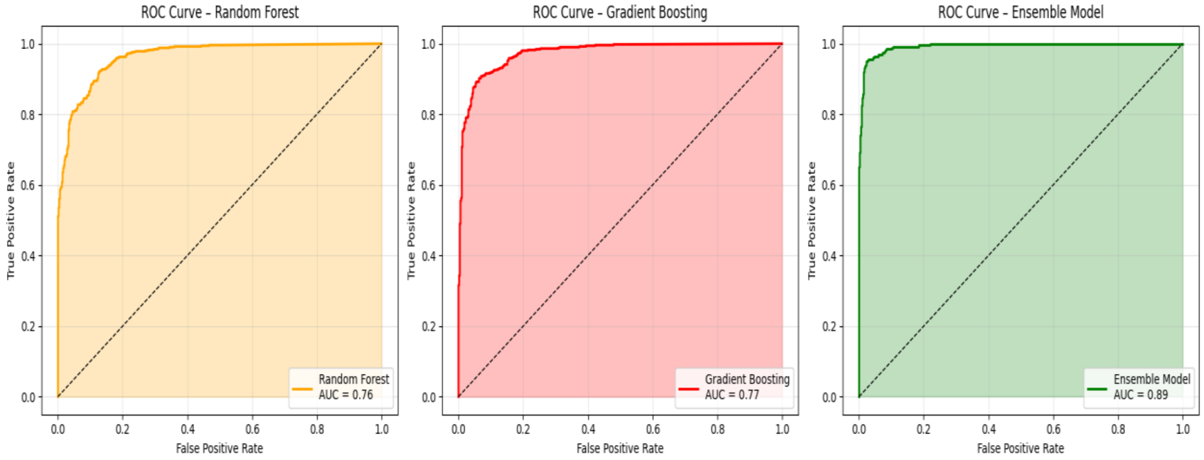

Figure 6. ROC curve of proposed ensemble machine learning model

The multi-subplot ROC visualization shows the classification performance of the Random Forest, Gradient Boosting, and Ensemble machine learning models by plotting the True Positive Rates (TPR) and False Positive Rates (FPR) of the three models at varying probability thresholds. A shaded area indicating the AUC (Area Under the Curve) is also provided in each subplot and measures the total amount of discrimination of each of the models. The Random Forest curve presents a smooth and consistent separation with the AUC of 0.76, which is considered to have a moderately strong predictive ability. The Gradient Boosting model shows a very steep increase in TPR in the presence of a small increase in FPR thus leading to a higher AUC of 0.77 reflecting higher performance and better learning of underlying patterns in the data. Ensemble model performs the best, its AUC is 0.89 and the curve that fits the upper-left side of the ROC space indicates the good separation of positive and negative classes. All these plots demonstrate that the Ensemble approach is a strong predictor with high accuracy levels because the plots combine the strengths of the different underlying base models to produce the best classification outcomes.

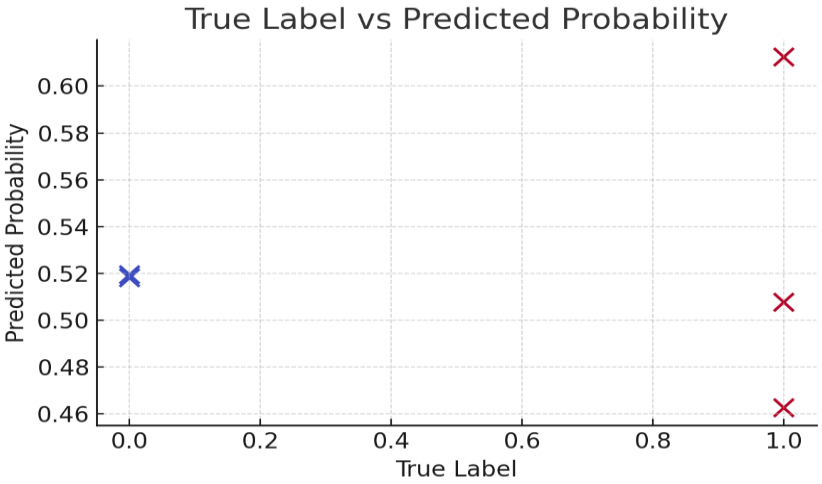

Figure 7. Prediction probability of proposed ensemble machine learning algorithm

The visualization in figure 7 shows the model predict live birth probabilities for individual IVF patients. The scatter plot compares true labels with predicted probabilities, revealing overlap that suggests inconsistent confidence and potential misclassification.

Conclusion

This study presented an AI-driven prediction framework to estimate the likelihood of live birth outcomes in couples undergoing IVF or ICSI treatment for the first time. Using the publicly available HFEA dataset, we applied advanced pre-processing through Auto Label Encoding and evaluated multiple machine learning algorithms to identify the most effective predictive model. Classical classifiers such as Random Forest, Gradient Boosting and proposed ensemble machine learning algorithm were examined, and their performance was assessed using accuracy, precision, recall, F1-score, ROC curves, and confusion matrices. Compared to individual models, the ensemble achieved superior accuracy (79%), precision (77%), recall (76%), and F1-score (76.49%), along with a substantially higher AUC-ROC value of 0.89. These findings confirm that combining multiple learning paradigms enhances the robustness of predictions, minimizes model bias, and better captures complex, non-linear patterns associated with IVF success rates. Overall, the proposed model demonstrates strong potential as a decision-support tool for clinicians and fertility specialists, improving the cost-effectiveness of treatment planning by empowering couples with early, data-driven success estimates.

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Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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