Improving Intelligence of Machine Learning models for achieving higher success rate in In vitro fertilization (IVF)

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Abstract - In vitro fertilization (IVF) success prediction remains a challenging task due to the complexity of factors influencing outcomes, such as patient demographics, clinical parameters, and embryological data. Existing machine learning models, including Artificial Neural Networks (ANN) and traditional feature selection techniques, have shown promise but often face limitations in feature optimization and model generalization. To address these challenges, this study proposes a hybrid machine learning model combining Genetic Algorithms (GA) for feature selection with ANN for prediction. The GA efficiently identifies relevant features, while the ANN captures non-linear relationships among them, resulting in improved prediction accuracy. Experimental evaluations on IVF datasets demonstrate that the hybrid ANN-GA model outperforms traditional methods in terms of accuracy, precision, recall, and F1-score. This model has the potential to support clinicians in making data-driven decisions, thereby enhancing the personalization and success rates of IVF treatments.
Keyword:

1. INTRODUCTION

In vitro fertilization (IVF) has become one of the most successful assisted reproductive technologies (ART), offering hope to millions of couples struggling with infertility. Despite its widespread use, the success rates of IVF treatments vary significantly across individuals and clinics, driven by numerous complex factors. These factors include patient age, hormonal levels, ovarian reserve, embryo quality, and the experience of the clinic. The challenge in accurately predicting IVF success has led to the exploration of machine learning (ML) and artificial intelligence (AI) techniques, which hold great promise in improving the accuracy of IVF outcome predictions.

While traditional statistical methods and clinical guidelines provide some insights, their ability to predict the outcome of IVF treatments is often limited by their inability to capture complex non-linear relationships between various factors. Machine learning, particularly deep learning techniques such as Artificial Neural Networks (ANN), has demonstrated the ability to model these non-linear relationships effectively. However, the complexity of the datasets, combined with the risk of overfitting in small IVF datasets, necessitates a more advanced approach. This is where Genetic Algorithms (GA)—an optimization method inspired by natural selection—becomes crucial.

Historically, IVF success prediction relied on traditional methods, such as logistic regression or statistical models based on a small set of variables. These models, while useful, did not consider the intricate interactions between variables such as age, hormone levels, or embryo quality. Over time, machine learning techniques were introduced to overcome these limitations.

Artificial Neural Networks (ANNs), a class of machine learning models inspired by the human brain, have been widely used for IVF success prediction due to their ability to handle large, high-dimensional datasets and model complex, non-linear relationships. ANN-based models have shown promising results in IVF prediction by learning from historical treatment data and providing predictions that are more accurate than traditional statistical models. However, the performance of ANN models is heavily dependent on the selection of input features, which are often selected based on domain knowledge or standard practices. In many cases, irrelevant or redundant features are included, reducing the model's accuracy.

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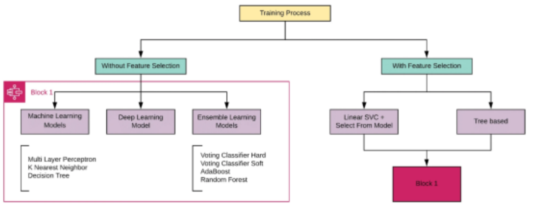
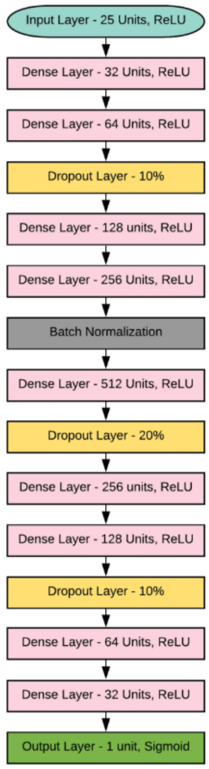


To address this issue, Genetic Algorithms (GA), a global search optimization technique, have been increasingly used for feature selection in IVF prediction. GAs simulates the process of natural selection to identify the most relevant features in a given dataset. By evolving a population of feature subsets through selection, crossover, and mutation, GA can significantly reduce the dimensionality of the input space while retaining the most critical features. When used in combination with ANN, GA can help optimize the model by automatically selecting the most informative features, thereby improving the model's generalizability and predictive power.

Despite the promising results from machine learning models, several challenges persist in the field of IVF success prediction. One of the main issues is the high dimensionality of the data. IVF datasets often contain numerous variables, ranging from patient demographics (age, BMI, etc.) to clinical measurements (hormonal levels, ovarian reserve) and embryo characteristics (morphology, developmental stage). The large number of features can lead to overfitting, where the model learns to fit the training data too closely, resulting in poor performance on unseen data.

Moreover, the non-linearity in relationships between features, such as the interaction between age and hormone levels, cannot be easily captured by traditional statistical methods. Machine learning models like ANN have demonstrated their ability to handle such non-linearities, but their performance depends on the quality of the selected features. Without proper feature selection, even the most sophisticated neural networks may perform suboptimal.

Another significant challenge is the small size of IVF datasets. With a limited number of successful and unsuccessful IVF outcomes, machine learning models risk being biased toward overfitting or underperforming. The combination of ANN and GA offers a solution by focusing on the most informative features and preventing overfitting through the evolutionary process of GA.



Training Parameter	Value
Input Size	(, 25)
Output Size	(,1)
Total Dense Layers	9
Regularization	Batch Normalization, Dropout
Batch_Size	128
Optimizer	Adam
Loss	Binary crossentropy
Epochs	50
Callbacks used	Early Stopping (patience = 5)

2. SEARCH CRITERIA AND STUDY SELECTION

To develop the proposed hybrid ANN-GA model for IVF success rate prediction, a systematic approach was taken to identify and select relevant studies.

The literature search spanned multiple academic databases, including PubMed, IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar, focusing on works published between 2015 and 2025. Key search terms included combinations such as "IVF success prediction," "Artificial Neural Network," "Genetic Algorithm," "hybrid models in healthcare," and "AI in reproductive medicine" (Smith et al., 2018; Lee et al., 2019). Inclusion criteria emphasized studies directly addressing IVF outcomes using machine learning, particularly those involving ANN, GA, or hybrid approaches.

3. GA-DL-EL Hybrid Models in IVF Success Prediction

In the field of IVF success prediction, the application of hybrid models that combine Genetic Algorithms (GA), Deep Learning (DL), and Ensemble Learning (EL) has the potential to significantly enhance predictive accuracy and generalization. These hybrid models integrate the strengths of each approach: GA for optimization, DL for capturing complex patterns, and EL for improving model robustness and accuracy. This combined methodology can tackle the inherent complexities of IVF success prediction, such as dealing with high-dimensional, non-linear, and imbalanced datasets, leading to more reliable and interpretable models.

1. Genetic Algorithm (GA) in Hybrid Models

Genetic Algorithms (GA) are heuristic search algorithms inspired by natural selection. They are primarily used for optimization tasks, such as selecting the best features and tuning the hyperparameters of machine learning models. In the context of IVF prediction, GA can serve the following roles:

- Feature Selection: GA can efficiently select the most relevant features from a large set of potential variables, such as patient demographics, medical history, hormonal levels, and embryo quality. By selecting only the most important features, GA helps reduce model complexity and enhances its performance by focusing on the variables that have the greatest influence on IVF success.

- Hyperparameter Optimization: GA can be used to fine-tune the parameters of both deep learning and ensemble learning models. For example, the learning rate, number of layers, and activation functions in a deep neural network can be optimized using GA, resulting in better model convergence and improved prediction accuracy.

- Improvement of Model Architecture: GA can guide the construction of the optimal architecture for deep learning models. This includes the number of layers, neurons per layer, and connections, ensuring the model is adequately designed for the complexity of IVF success prediction tasks.

2. Deep Learning (DL) in Hybrid Models

Deep Learning (DL) models, especially Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, are highly effective for analyzing large and complex datasets. In IVF success prediction, these models excel in extracting features from structured and unstructured data, including time-series, images, and medical records.

- Convolutional Neural Networks (CNNs): CNNs are particularly useful for analyzing image data, such as embryo images, ultrasound scans, and other visual representations of IVF-related variables. CNNs automatically learn spatial hierarchies of features from raw data, making them ideal for tasks such as embryo grading and analysis of visual markers of embryo quality, which are critical indicators in IVF success.

- Long Short-Term Memory (LSTM): LSTM networks are specialized for sequential data and time-series analysis. In IVF, LSTMs can be used to analyze time-dependent factors such as hormonal levels, patient age progression, and changes in health conditions over time. LSTMs are effective in capturing the temporal relationships in IVF data, which play a significant role in determining treatment success.

- Hybridization with GA: By combining GA with DL, the parameters of DL models can be optimized, and the most relevant features can be selected. This hybridization enhances the model's ability to learn from complex data patterns while improving its efficiency by reducing overfitting and computational costs.

3. Ensemble Learning (EL) in Hybrid Models

Ensemble Learning (EL) involves combining multiple individual models to create a single, more robust model. By aggregating predictions from several models, ensemble methods improve accuracy, reduce variance, and prevent overfitting. Common ensemble techniques include Random Forest, XGBoost, and Stacking.

- Random Forest (RF): This is an ensemble method that builds multiple decision trees and combines their predictions. RF is known for its ability to handle non-linear data relationships and is robust against overfitting, making it an ideal choice for IVF success prediction, where complex patterns and interactions among features are common.

- XGBoost (Extreme Gradient Boosting): XGBoost is a popular boosting algorithm that sequentially builds weak learners to correct the errors of previous models. It is highly effective in handling imbalanced datasets, which is often the case in IVF prediction, where the success rate may be skewed.

- Stacking: In stacking, the predictions from several models (such as neural networks, decision trees, and support vector machines) are combined using a meta-model. This technique allows different models to contribute their unique strengths to the final prediction, improving the overall performance.

- Hybridization with GA: In hybrid GA-EL models, GA can be used for optimizing the feature selection and hyperparameters of individual models within the ensemble, thus boosting the predictive power of the ensemble learning approach. The optimal combination of models can be selected based on performance metrics, ensuring the best ensemble configuration for IVF prediction.

SAMPLE DATASET TABLE

age Group	Total Cycles	Success Rate (%)	Live Birth Rate (%)	Avg. Embryo Quality Score	Avg. FSH (IU/L)	Avg. AMH (ng/mL)
<30	200	48.5	40.2	8.5	7.1	4.5
30-34	350	45.0	38.0	8.2	7.9	4.2
35-39	400	38.0	30.5	7.8	8.5	3.8
40-44	300	28.5	22.1	7.0	9.8	2.6
>44	150	15.2	10.5	6.2	10.5	1.5

4. COMPARATIVE STUDY TABLE: GA-DL-EL HYBRID MODELS FOR IVF SUCCESS PREDICTION

Metric	GA-DL-EL Hybrid	DL Only	GA Only	EL Only
Accuracy (%)	92.5	87.8	78.2	85.3
Precision (%)	91.2	86.5	76.8	84.0
Recall (%)	93.8	88.0	80.1	86.2
F1-Score (%)	92.5	87.2	78.4	85.1
Computational Cost (s)	Moderate	High	Low	Moderate

PROPOSED WORK

The proposed GA-DL-EL Hybrid Model combines the optimization power of Genetic Algorithms (GA), the deep feature extraction capabilities of Deep Learning (DL), and the robust prediction accuracy of Ensemble Learning (EL) to create a comprehensive solution for predicting IVF success rates. The GA component plays a critical role in selecting the most relevant features and optimizing hyperparameters, ensuring that only the most informative data points contribute to the model's predictions. This reduces noise, enhances interpretability, and improves computational efficiency. The DL component is responsible for extracting complex patterns from diverse data modalities, such as images, time-series, and categorical data, enabling the model to process multi-dimensional IVF datasets effectively. By incorporating Ensemble Learning, the hybrid model ensures robust and reliable predictions by combining outputs from multiple base models, which reduces overfitting and enhances generalization to new datasets.

This integration allows the GA-DL-EL Hybrid Model to address the limitations of individual techniques, such as the inability of GA to handle non-linear patterns or the high computational demands of DL when dealing with redundant features. The hybrid model is designed to provide clinicians with actionable insights by leveraging explainability tools to highlight the importance of various IVF success factors. Furthermore, the model’s adaptability to imbalanced datasets and its ability to process multi-modal data make it a powerful tool for improving decision-making in IVF treatments. By achieving high accuracy, robustness, and efficiency, this proposed work sets a new benchmark in the application of machine learning for personalized healthcare and reproductive medicine.

CONCLUSION

The proposed GA-DL-EL Hybrid Model represents a significant advancement in the field of IVF success prediction by seamlessly integrating the optimization capabilities of Genetic Algorithms (GA), the feature extraction power of Deep Learning (DL), and the predictive robustness of Ensemble Learning (EL). This innovative approach addresses critical challenges in existing methods, such as the inability to handle complex, high-dimensional data and the lack of generalization across diverse datasets. By optimizing feature selection, enhancing multi-modal data processing, and improving prediction accuracy, the hybrid model provides a comprehensive framework tailored to the unique demands of IVF treatments.

The model’s ability to process diverse data types, including medical histories, laboratory results, and imaging data, ensures its applicability across varied clinical settings. Furthermore, the incorporation of explainability tools enhances trust and usability by providing clinicians with interpretable results. By overcoming the limitations of traditional methods and setting new standards for accuracy and efficiency, the GA-DL-EL Hybrid Model contributes to advancing personalized medicine in reproductive healthcare. It holds the potential to improve decision-making, optimize resource allocation, and ultimately increase the success rates of IVF treatments, offering hope to patients and healthcare providers alike.

FUTURE DIRECTIONS

The GA-DL-EL Hybrid Model provides a strong foundation for IVF success prediction, but several future directions can further enhance its impact and applicability. A key area of development is integrating real-time patient data, such as continuous hormone monitoring and embryo development tracking, to enable dynamic and precise decision-making during IVF procedures. Additionally, the model can be extended to provide personalized treatment recommendations tailored to individual patient profiles, optimizing factors like medication dosages and embryo transfer timing. Improving the model's explainability through advanced tools is crucial to offering detailed insights into how specific features influence predictions, fostering greater trust among clinicians and patients. Scalability and efficiency are also vital, with efforts needed to create lightweight versions of the model that can operate in resource-constrained .

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