Enhancing IVF Success: Factors and Predictive Models

Investigating Age, Sperm Quality, and Embryo Development in Fertility Treatments

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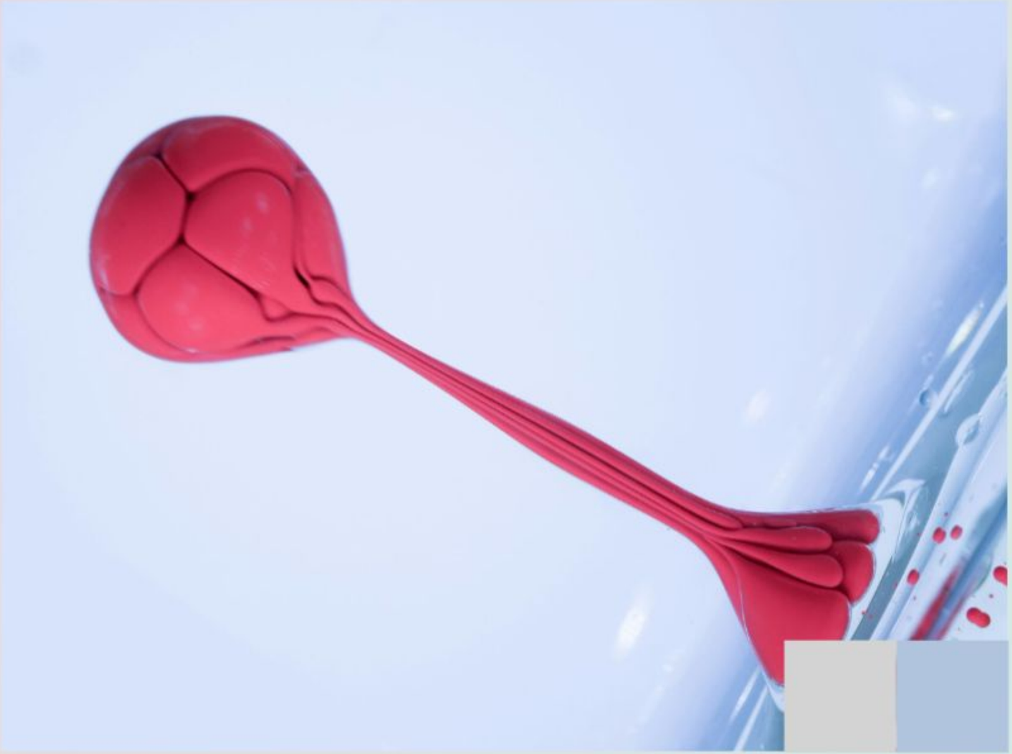
Table of Contents



Background

This study examines factors influencing IVF success, particularly embryo age (4 vs. 5 days), patient and spouse age, age differences, and sperm quality. By analyzing these variables, we aim to understand their impact on clinical pregnancy rates through statistical analysis and predictive modeling.

Analysis Aims

- Identifying significant elements for a successful IVF process
- Understanding the impact of age, sperm quality, and embryo age on IVF success
- Formulating models for predicting and enhancing IVF success

Statistical Methods

- Logistic Regression Analysis
- Random Forest Evaluation
- Support Vector Machine Model

Data Collection

Link to the dataset HERE

Clinical data from over 5000 IVF cases

Demographic and various other relevant data points

Procedural and treatment data

Longitudinal and repeated measures

Key Findings

Age and IVF Success:

Older patient age significantly reduces IVF success rates, highlighting the critical need for age-specific treatment approaches.

Oocyte and Embryo Quality:

Poor oocyte quality and suboptimal embryo age (4 or 5 days) are major barriers to IVF success, underscoring the importance of quality control in these areas.

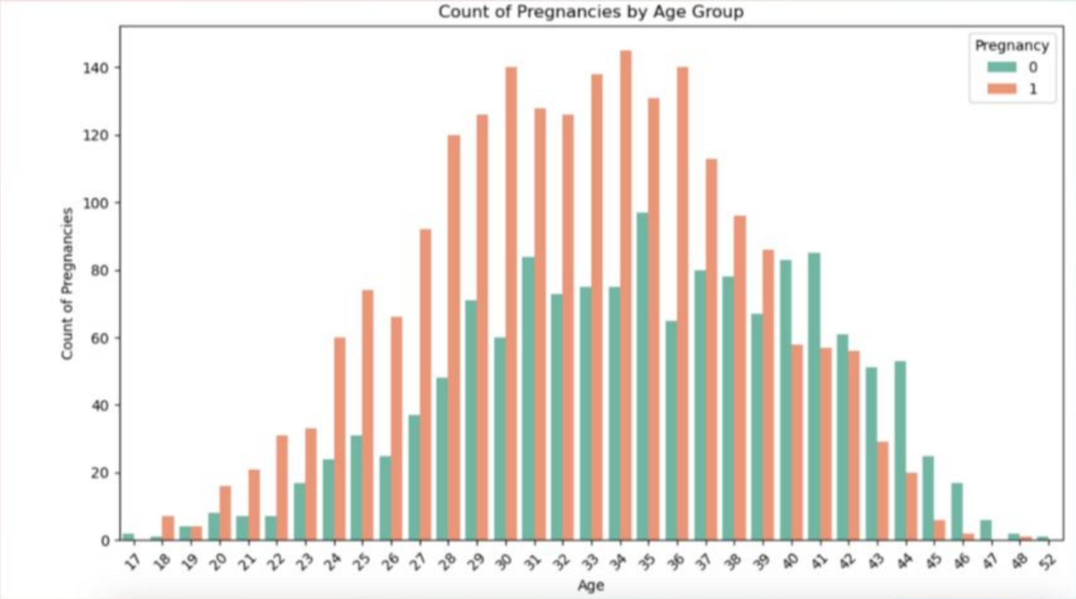
Sperm Quality:

Normal sperm evaluation correlates with higher IVF success rates, emphasizing the role of sperm quality in successful fertility treatments.

Age and IVF Success

This graph shows the age distribution of patients and highlights age-related trends.

This plot reveals how age correlates with pregnancy success, providing insights for tailored fertility treatments.



Statistical Analysis

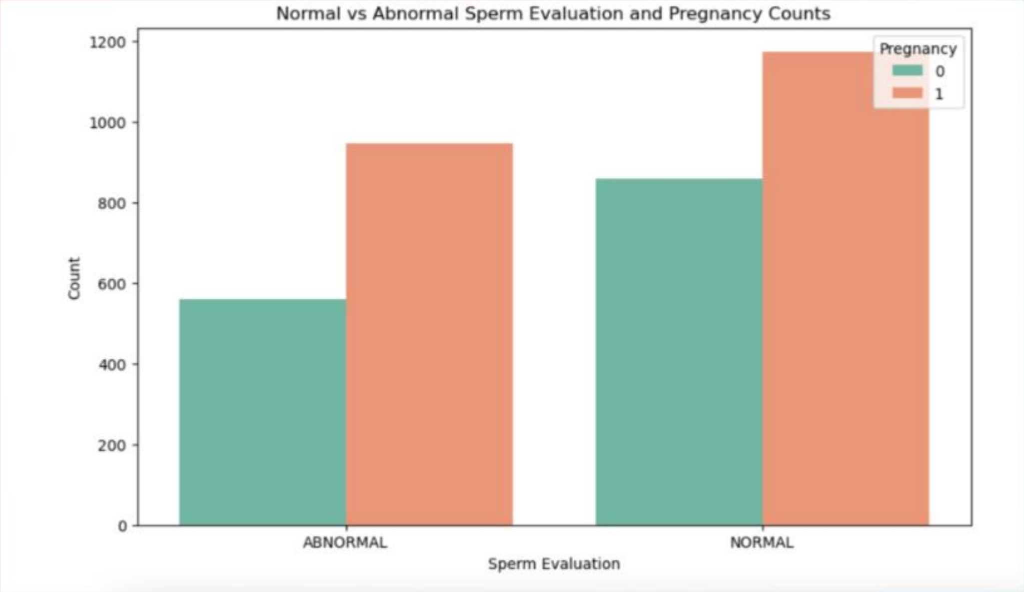
I conducted a t-test comparing the ages of patients with successful vs. unsuccessful IVF outcomes.

Results showed a significant difference in age between the two groups (T-statistic: -12.57, P-value: 1.65e-35).

Sperm Quality

Data Cleaning:
Converted all non-normal sperm evaluations to "ABNORMAL" to simplify the analysis. This ensures clear differentiation between normal and abnormal sperm quality in the dataset.

Data Visualization:
Created a count plot to compare pregnancy outcomes between normal and abnormal sperm evaluations. This visualization helps illustrate the relationship between sperm quality and pregnancy success.



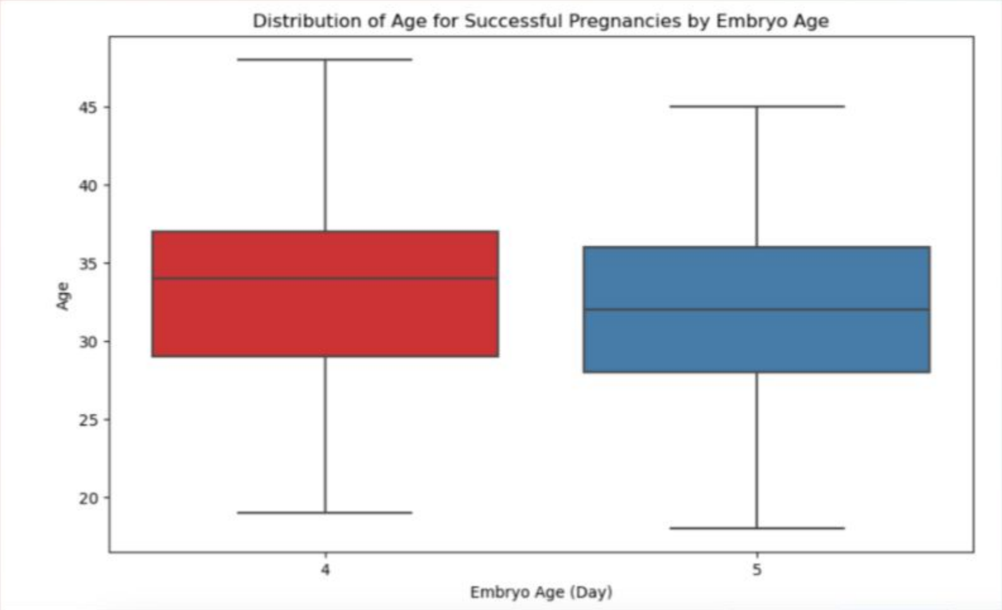
Findings

Individuals with normal sperm evaluations show higher pregnancy rates compared to those with abnormal evaluations, emphasizing the importance of sperm quality in IVF success.

Oocyte and Embryo Quality

Data Filtering:
Filtered the dataset to include only successful pregnancies and non-null age values to focus the analysis on relevant data points.

Data Visualization:
Created a boxplot to display the distribution of maternal age for successful pregnancies, categorized by embryo age (day 4 vs. day 5). This visualization highlights any age-related trends in successful pregnancies based on embryo age.



Findings

The boxplot indicates that successful pregnancies are more prevalent with day 4 embryos compared to day 5 embryos. This suggests that the timing of embryo transfer plays a crucial role in the success rates of IVF procedures.

Data Preprocessing Steps

Remove Duplicates

Dropped duplicate columns from the dataset to ensure clean and unique feature representation.

Convert Categorical to Numeric

Transformed the 'SPERM EVALUATION' column from categorical to numeric values (1 for 'Normal', 0 for 'Abnormal') for compatibility with machine learning algorithms.

Impute and Scale Data

Created pipelines to handle missing values and scale numerical data. Used median imputation and standard scaling for numerical features. Applied most frequent imputation and one-hot encoding for categorical features.

Column Transformation

Combined numerical and categorical preprocessing steps using a ColumnTransformer to ensure consistent and streamlined data preparation for model training.

Apply Preprocessing

Fitted and transformed the training data, and transformed the test data using the defined preprocessing pipelines, ensuring the data is ready for model training.

Statistical Modeling Results

Accuracy		Precision for successful IVF		Recall for successful IVF	
62%	Logistic Regression	64%	Logistic Regression	81%	Logistic Regression
62%	Random Forest	64%	Random Forest	80%	Random Forest
61%	Support Vector Machine	63%	Support Vector Machine	83%	Support Vector Machine

SMOTE Re-evaluation

Overview:

- SMOTE Technique: Implemented Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance in the dataset.
- Objective: Enhance model performance by generating synthetic samples for the minority class (Unsuccessful IVF) to balance the dataset.

Methodology:

- Implementation: Applied SMOTE to the training data (X_train and y_train) to oversample the minority class.
- Models Used: Logistic Regression, Random Forest, and Support Vector Machine were trained on the resampled data to evaluate performance.

SMOTE RE-EVALUATION RESULTS

Previous Precision for successful IVF

64% Logistic Regression

64% Random Forest

63% Support Vector Machine

SMOTE Precision for successful IVF

66% Logistic Regression

66% Random Forest

66% Support Vector Machine

Analysis

Impact: SMOTE effectively balanced the dataset, resulting in improved precision, recall, and F1-score for both Unsuccessful and Successful IVF outcomes.

Recommendation: Continued use of SMOTE or similar techniques is advised to mitigate class imbalance systematically and enhance the overall accuracy and reliability of IVF success prediction models.

Model Insights after Re-Evaluation

Model Performance Comparison:

- Logistic Regression: Demonstrated moderate performance with balanced precision but lower F1-scores.
- Random Forest: Consistently outperformed other models with higher F1-scores, particularly for predicting positive fertility outcomes.
- Support Vector Machine (SVM): Achieved balanced precision across classes but slightly lower F1-scores compared to Random Forest.

Next Steps for Improvement:

- Further optimize models through hyperparameter tuning.
- Consider ensemble methods to enhance predictive accuracy.
- Generalize findings to broader datasets for robust and reliable fertility predictions in clinical settings.

CONCLUSION

Through our analysis leveraging Logistic Regression, Random Forest, and Support Vector Machine models, coupled with SMOTE for addressing class imbalance, we successfully predicted IVF fertility outcomes. Notably, we confirmed that patient age, oocyte age, and sperm evaluation significantly influence these outcomes. Random Forest consistently demonstrated superior performance, particularly in predicting positive fertility results.

Moving forward, optimizing models with hyperparameter tuning and ensemble methods promises to enhance accuracy and extend the applicability of our findings in clinical settings. This study advances decision-making in IVF treatment by providing insights into critical predictors of success.