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International Journal of Innovations in Science & Technology

RESEARCH & INNOVATION DIVISION

IJIST

Clinical Prediction of Female Infertility Through Advanced Machine Learning Techniques

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Citation | Khan. F. M, Akhter. M. S, Khan. I. U, Haider. Z. A, Khan. N. H, "Clinical Prediction of Female Infertility Through Advanced Machine Learning Techniques", IJIST, Vol. 6 Issue. 2 pp 900-917, June 2024

Received | June 16, 2024 **Revised |** June 25, 2024 **Accepted |** June 26, 2024 **Published |** June 28, 2024.

Infertility in females implies failure by such women to conceive even after having at least one year of intercourse without using any contraceptives. Infertility can be caused by a variety of factors, including ovulation problems, blocked fallopian tubes, hormone imbalances, and abnormalities of the uterus and so on. Infertility can negatively impact people's emotional, psychological, and social well-being. Our proposed study utilizes advanced machine learning techniques to present an innovative and novel method for predicting female infertility. We analyzed a dataset with medical attributes related to reproductive health using logistic regression, Naive Bayes, Support Vector Machines (SVM), and Random Forest algorithms. The Random Forest algorithm achieved an outstanding accuracy rate of 93%, with its exceptional capabilities. The findings show that in the future, this model can be used to diagnose infertility early and provide personalized treatment recommendations. The results of this study have practical implications for reproductive healthcare, as well as providing much-needed support to infertile couples and individuals.

Keywords: Infertility; Machine Learning Techniques; Random Forest; SVM, Logistic Regression and Naïve Bayes.

Introduction:

Infertility has become a pressing issue affecting numerous couples globally, prompting diverse approaches to address its complexities. Recent data from the National Center for Health Statistics (NCHS) indicate that infertility affects 8.8% of the American population. According to a study conducted in the United Kingdom, the prevalence of female infertility was found to be 12.5%, while the prevalence of male infertility was estimated to be 10.1% [1]. Extensive research has explored various diagnostic models in reproductive medicine, reflecting the dynamic nature of medical science and its ongoing adaptation to new ideas and challenges. The following are certain methodologies that were prevalent during the specified period or have been subject to contemporary scholarly investigation: The methods discussed encompass several aspects of reproductive medicine, such as oocyte cryopreservation (commonly known as egg freezing), surrogacy, fertility medicines, and fertility treatments. These procedures include Intrauterine Insemination (IUI), Intracytoplasmic Sperm Injection (ICSI), Gamete Intrafallopian Transfer (GIFT), Preimplantation Genetic Testing (PGT), and In Vitro Fertilization (IVF). To diagnose infertility and choose appropriate treatment options, a variety of laboratory tests are commonly employed to enhance assessment and discover suitable methods. These diagnostic tests are crucial for identifying the root causes of infertility, tracking the effectiveness of therapies, and ensuring the safety and efficacy of treatment procedures. Hormone tests, sperm analysis, Hysterosalpingogram (HSG), ultrasound imaging, genetic testing, ovulation monitoring, infectious disease screening, endometrial biopsies, and Preimplantation Genetic Testing (PGT) are some of the tests that are done in a lab to analyze and evaluate. Every couple in the world couldn't afford these tests and procedures due to their high cost. Therefore, predicting the likelihood of infertility in women remains a challenging task that is also cost-effective. Infertility is defined as the inability or failure to achieve pregnancy after six months to one year of unprotected sexual intercourse [2].

Infertility affects one in six couples globally during their reproductive years [3]. It has profound effects on couples, leading to depression, social isolation, and personal challenges. The complexity of infertility depends on factors such as age, duration of attempts to conceive, and other significant considerations [4][5]. Infertility affects approximately 15% of couples, with about half of these cases attributed to female factors. Women who are infertile suffer enormous psychological stress, which can lead to depression, pain, and discrimination [6]. Infertility is a widespread issue affecting many individuals globally. According to a recent report by the World Health Organization (WHO), approximately 17.5% of the adult population worldwide experiences infertility. This highlights a critical need for accessible and high-quality fertility care to address this significant public health challenge. However, to overcome this issue, various methods have been proposed to diagnose infertility which include Assisted Reproductive Technology (ART) method. It makes a significant contribution to population growth. The International Committee on ART Terminology (ICMART) released a dictionary of ART terminology in 2006 that included global consensus definitions for summarizing the ART procedure [7]. ARTs that involve fertilizing eggs, sperm, and embryos outside the body include procedures such as In Vitro Fertilization (IVF) and Intracytoplasmic Sperm Injection (ICSI). The utilization of assisted reproductive technologies has witnessed a surge due to the desire to save eggs or embryos for later conception in life. According to the cited source, the global number of infants born as a result of ART exceeds 10 million. The prevalence of ART in the United States is estimated to be around 2.3% among newborns [8]. Experts carefully select a tailored treatment plan based on each couple's individual circumstances. Infertility management options often entail significant costs and potential side effects, typically recommended when natural conception is not achievable for a woman. Predictive models are commonly advocated for utilization in medical decision-making due to the presence of a clinical obstacle encountered by gynecologists during the process of conducting such comparisons [9].

To address these challenges and simplify decision-making, we have devised a model capable of predicting the likelihood of infertility in women with ease. Our approach utilizes a cost-effective and accessible machine learning framework, leveraging a proprietary dataset collected with authorization from Peshawar Infertility Hospital in Pakistan. By refining our model with key parameters, we have enhanced its capability to deliver accurate predictions concerning female infertility.

Objectives and Novelty of the Proposed Study:

The primary contribution and unique aspect of this research are outlined as follows:

- To Develop a comprehensive dataset comprising medical attributes related to reproductive health to facilitate the study of infertility in women.
- To Develop predictive models using machine learning algorithms to identify infertility risks in women based on the newly created infertility dataset and assess their accuracy and effectiveness.
- Evaluate the performance of multiple machines learning algorithms, including Logistic Regression, Naive Bayes, Support Vector Machine (SVM), and Random Forest, to determine the most accurate model for infertility prediction.
- For the first time, we conducted a study on female infertility using a different dataset than those used by other researchers in their studies. We employed machine learning models and develop a dataset on female infertility by collecting data from Hospitals. This dataset allows us to create predictive models that can accurately predict infertility in females.

Related Work:

Various predictive models have been presented and evaluated for predicting infertility in women. For example, the Random Forest (RF) model was the most statistically significant in the IVF / ICSI treatment. Factors such as age, hormone status, endometrial density, and duration of infertility were particularly significant. Older women had lower endometrial thickness and fewer follicles [10]. In another study, the authors used Random Forest Regression (RFR) to predict ovarian response in 680 elderly infertile patients. They examined 12 clinical measurements and found that Preovulatory Follicle Count, Antral Follicle Count, And Anti-Mullerian Hormone (PFC, AF, AMH) were the most significant predictors of ovarian response.

This approach allows patients to predict outcomes during controlled ovulatory hyperstimulation, as demonstrated by Wei and colleagues[11]. Another study employed sperm analysis to predict male fertility rates using deep learning and a Convolutional Neural Network (DNN). Naseem et al. [12] found that the results are highly predictive in terms of sperm head detection and sperm prediction, which could be useful for automated insemination workflow. Excessive alcohol use might have a negative impact on a woman's fertility. Alcohol has an immediate effect on the male reproductive system and can cause hormonal abnormalities. Alcohol damages the male genetic system, resulting in a reduction in sperm count. Furthermore, alcohol may be harmful to human health, particularly sexual and reproductive health. The size of the genitalia might shrink as a result of alcohol addiction. Furthermore, alcohol can injure the cells that produce sperm, resulting in infertility. Furthermore, alcohol can lower a woman's fertility, which can be problematic for those who are trying to conceive. Continuing to drink while pregnant increases the risk of miscarriage and can lead to preterm birth and low birth weight infants. Furthermore, an alcoholic mother's kid has a 40% chance of developing the fetal condition known as alcohol syndrome. These individuals have heart and cognitive issues, low hormone levels, and poor behavior Zhang et al. [13].

The researchers developed a model using machine learning and statistics to identify risk factors for early-term pregnancy loss in FET cycles. They also evaluated the importance of each model component in predicting pregnancy loss Ozer and others [14]. In this study, we developed machine learning models to predict clinical pregnancies during In Vitro Fertilization (IVF), as demonstrated by C.-W. Wang et al. [15]. The success rate of pregnancy resulting from in vitro fertilization (IVF) is estimated to range from 30% to 70%, depending on the patient's age and the various protocol regimens employed. As the world's infertility rates continue to rise, AI is playing an increasingly important role in evaluating women's reproductive health. This review highlights AI's importance in areas such as follicular monitoring and timing of transplants, as well as ultrasound-based pregnancy outcome prediction. It also highlights limitations and challenges that need to be addressed, while also emphasizing the potential for faster and more personalized assessments in the future [16].

Ultrasound is crucial for women's reproductive health as it aids in assessing ovarian reserve and endometrial receptivity (ER) [17]. However, Tubal patency in conjunction with normal ovarian function in the presence of normal sperm analysis results in female infertility [18]. The focus was on mental health aspects of fertility treatment, which, despite its importance, is often overlooked. Infertility is a stressful experience for couples and the aim of the study was to look at anxiety and depression risk factors in female infertility patients [19]. Polycystic ovarian disease is another cause of infertility; it is a form of reproductive disorder that can increase a woman's likelihood of becoming infertile. Additional polycystic ovary syndrome complications include hyperandrogenic hormones, type 2 diabetes, and cardiovascular disease Vats and others [20]. The psychological factors associated with anxiety and depression in female infertility patients were investigated in one study by Simi et al. [21] utilized two psychological tests: the Self-rating Depression Scale (SDS) and the hospital anxiety depression scale (HADS).

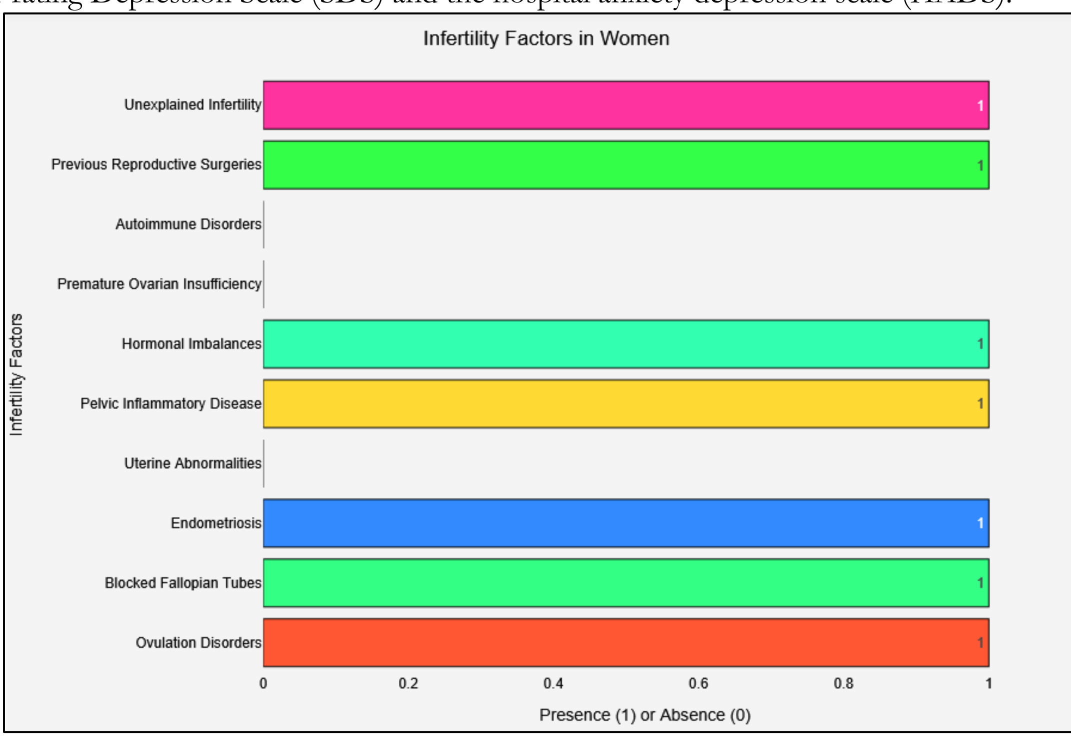

Figure 1: Infertility Factor in Women

Another author used an Artificial Intelligence (AI) model to select the most effective IVF-ET treatments for patients, taking into account new and recurrent cases. The study compared ten AI algorithms used to predict pregnancy outcomes and evaluated the significance of patient characteristics in the models [22]. In addition, Testicular Sperm Extractions (TESE) play a crucial role in treating male infertility.. TESE is an invasive procedure that has a success rate of up to 50%. However, no clinical and laboratory model is powerful enough to predict sperm retrieval success in TESE [22].

In another research on TESE (Microdissection Testicular Sperm Extraction) for Non-Osteospermia, the goal was to predict TESE success rates using optimal logistic models. Patient age, FSH (serum FSH concentration) and Johnsen's (JS) score were significant predictors of TESE success, which can reduce the need for unnecessary surgery [23]. The author also created another model to predict live birth using an AI neural network platform [24]. Another proposed predictive model for IUI treatment was based on MvLR (Multivariable Logistic Regression) analysis and statistical techniques that can estimate relative weights for independent variables to predict pregnancy [25]. Logistic regression has been employed by a number of researchers to forecast success rates [26]; [27]; [28].

Machine learning-based algorithms can successfully handle medical decision-making data, including clinical predictions [29]; [30]. For this purpose, Liao et al. [31] created a machine learning risk scoring algorithm for diagnosing and treating infertility. Eight key infertility features are screened by the algorithm, and weights are assigned to them based on the algorithm's feature selection algorithm. Features are selected using entropy-based features discretization and random forest. The algorithm predicts pregnancy outcomes based on the overall risk score, helping doctors choose more effective treatments. The algorithm also takes into account different age groups to improve accuracy, showing the potential of artificial intelligence in reproductive fields.

A researcher developed a predictive model for male infertility risk factors. According to the study, support vector machines and super learner algorithms outperformed other methods with AUC scores of 96% and 97%, respectively. Sperm concentration, follicle-stimulating hormone, luteinizing hormone, and genetic factors were key risk factors [32]. Computer technology has advanced rapidly, resulting in the widespread adoption of artificial intelligence in medicine. These emerging machine learning methods have proven to be superior to traditional approaches in terms of performance. Among these techniques, eXtreme Gradient Boosting (XGBoost) stands out as a well-regarded method that has found applications in the medical field. Healthcare data can be used for a variety of purposes, and it has gained a reputation for being very insightful [33]; [34].

The author developed their feature selection algorithm using a variety of techniques in order to improve the accuracy of IVF pregnancy predictions. To evaluate the predictive ability of these models, they utilized multilayer perceptron, support vector machines, C4.5 classification and regression trees, random forest, and 25 attributes. [35] found that the key characteristics of these models were substantially more predictive than those found in the existing literature. The researcher examined multiple classifiers to forecast the outcome of embryo implantation in In Vitro Fertilization (IVF). The study analyzed a total of 18 parameters: nine associated with patient characteristics and nine related to embryo features. Support Vector Machines (SVM), Decision Trees (DT), naive Bayes (NB), k-nearest neighbors (KNN), multilayer perceptron (MLP), and radial basis function (RBF) were among the classifiers used in this investigation. The classifiers were evaluated using ROC to see how well they performed. The NB and RBF classifiers performed better, as seen by their AUC values of 0.739% (0.036) and 0.712% (0.036), respectively. In a follow-up study, the team narrowed the traits down to 11 after sorting them by relative importance. This modification led to a marginal enhancement in the performance of the Naive Bayes (NB) classifier, yielding an accuracy of 80.4% and an Area Under the Curve (AUC) value of 0.756% (0.036)[36].

Nanni and others [37] assessed ten features and evaluated three distinct base classifiers (SVM, ANN, DT) as well as variants of these classifiers. For feature selection, they utilized SFFS (Sequential Forward Floating Selection). The ensemble method (Random Subspace DT) with only three features (Patient's Age, Subendometrial Volume, and Endometrial Vasculization/Flow Index) had a higher prediction accuracy (AUC) than other classifiers. The top model had an AUC of 0.85, but the dataset used in the study had relatively few treatment cycles. Authors Brás de Guimares et al. [38] conducted research to develop a predictive model of live birth following IVF/ICSI treatment using demographic and clinical data collected over 1193 treatment cycles between 2012 and 2019. On the basis of Pearson correlation, input variables such as the woman's age, the dose of gonadotropin, the number of eggs, the number of embryos, and the AF count were selected for the construction of an artificial neural network (ANN). Additionally, a decision tree model was developed. The ANN model achieved 75.0% accuracy with an AUROC curve (75.2%) and the decision tree model achieved 74.0% accuracy, resulting in a 74.9% accuracy of live birth probabilities prior to the first embryo transfer.

In this research paper, we developed predictive models using machine learning techniques and conducted a comparative analysis. Using our infertility dataset, we compared the performance of logistic regression, Naive Bayes, support vector machine, and Random Forest models. According to our findings, every model outperformed our expectations. Notably, this is the first study to compare well-established machine-learning models for predicting infertility using our unique dataset.

Material and Methods:

Dataset Description:

We collected data of 705 patients from Johar Khatoon Gynecologist Hospital, Peshawar (Pakistan). The process was performed with the approval of the competent authority, ensuring compliance to ethical standards and patient privacy. We have focused on various characteristics related to reproductive health in an effort to assist women with or without infertility. Collection of this data required each patient's informed consent and removal or anonymization of all personal identifiers to ensure confidentiality. This dataset consists of a variety medical attribute which are important in order to extensively understand what factors contribute how and where infertility arises.

Overall, we collected 705 medical data features. In our study we utilized a sub set of thirteen (13) principal attributes: Twelve (12) numeric-valued attributes and just one nominal valued attribute. These attributes were selected due to their relevance in providing valuable insights into reproductive health outcomes and their association with infertility. The twelve attributes with numeric values encompass various clinical and biochemical parameters that specify the reproductive health status of patients. Among these parameters, the age is an important one as suggested by other research studies along with BMI, Blood pressure levels or hormone levels and other health indicators. This single nominal-valued attribute is a categorical variable which classifies the patients according to one particular criterion related with their reproductive health. Table 1 provides a list of attributes. The table below provides a description of each attribute, including its name, classification (numeric or nominal), and a brief explanation of its relevance to infertility research. This predictive model aims to assist physicians in diagnosing and treating infertility more effectively.

Table 1: Infertility Dataset

Attribute	Description	Type
Patient ID	Unique identifier for each patient, used for case tracking.	Nominal
Age	Age of the patient, a crucial factor in fertility assessment.	Numeric
Ovulation Disorders	Variable indicating whether ovulation disorders, which can affect menstrual cycles, are present (1) or absent (0).	Numeric
Blocked Fallopian Tubes	A binary variable that represents whether or not the fallopian tubes are blocked, which can prevent fertilization.	Numeric

Endometriosis	Endometriosis, a condition that affects fertility, is represented as a binary variable that can either be present (1) or absent (0).	Numeric
Uterine Abnormalities	A binary variable that denotes whether uterine abnormalities that could impair implantation are present (1) or not (0).	Numeric
Pelvic Inflammatory Disease	A binary variable that denotes whether pelvic inflammatory illness, which can lead to infertility, is present (1) or absent (0).	Numeric
Hormonal Imbalances	Binary variable showing if hormonal abnormalities that disturb the menstrual cycle are present (1) or absent (0).	Numeric
Premature Ovarian Insufficiency	A binary variable indicating whether early ovarian insufficiency leading to infertility is present (1) or absent (0).	Numeric
Autoimmune Disorders	A binary variable that denotes whether autoimmune diseases that affect the reproductive system are present (1) or absent (0).	Numeric
Previous Reproductive Surgeries	A binary variable is employed to denote whether the patient has previously had reproductive procedures (1) or has not (0).	Numeric
Unexplained Infertility	A binary variable that represents the presence (1) or absence (0) of infertility that cannot be explained and has no known cause.	Numeric
Infertility Prediction	Variable with binary outcomes (0 or 1) based on the combination of the aforementioned characteristics and their influence on fertility.	Numeric

Proposed System:

The detection and addressing of infertility are of utmost importance due to the substantial impact it can have on people and couples. In order to tackle this matter, a comprehensive investigation was initiated, encompassing a total of 705 patient data. The dataset comprises patient identification of several numeric indicators associated with reproductive health, including ovulation irregularities, obstructed fallopian tubes, endometriosis, and other related factors. This study focuses on the most important element, which is a targeted variable called "Infertility prediction" that helps predict infertility results. It is important that this dataset includes both women with and without fertility issues.

Data Pre-Processing

To prepare the given dataset for analysis and machine learning model training, the following data pre-processing steps are taken:

Removing Duplicate Records: We removed duplicated data from dataset to ensure each patient record is unique to trained model on it.

Handling Null Values: We filled the missing and null values in the dataset filling them with suitable values e. g mean, median etc. or removing the rows/columns with missing data.

Feature Encoding: We converted categorical features into numerical values. Our dataset contains categorical labels ("fertility", "infertility") which need to be encoded into numerical values for machine learning algorithms to process.

Scaling Numerical Features: We normalized/standardized the numerical features to ensure that they are on a similar scale. This step is crucial for algorithms that are sensitive to the magnitude of the input features.

Splitting the Dataset: We divided the dataset into 80% and 20% ratios of training and testing sets to evaluate the performance of the machine learning model.

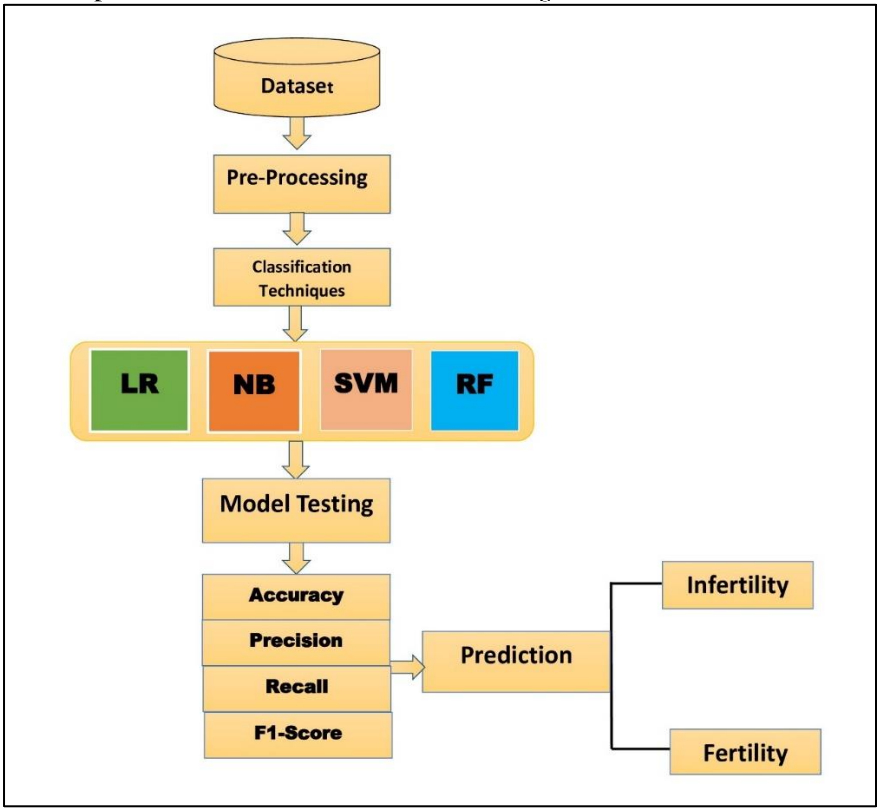

Figure 2: Proposed System

Statistics on the Dataset

The descriptive statistics of the dataset have significantly changed following the application of various preprocessing steps. The features of the dataset had initially diverse means and standard deviations, with some being binary indicating specific conditions, such as ovulation disorders or blocked fallopian tubes. Standard Scaler from scikit-learn was used for standardization where all numerical features were converted to have mean = 0 and std. deviation =1. Ensuring that each trait contributes equally to follow-up analyses and machine learning models results in more reliable predictors, eliminating bias from differing scales. Then, transformation retained the interpretability (of unique values and frequencies) in categorical dataset which improved consistency and reliability of whole dataset from analytical perspective.

Correlation Matrix

In addition, a correlation table is generated to assess the relationships between the numerous categories. Additionally, the correlation matrix permits the examination of interrelationships between the features present in the dataset. The "sns. heatmap()" function from the Seaborn library is used to generate the heatmap. This function incorporates annotations that exhibit the correlation coefficients within each individual cell. Furthermore, the utilization of a "coolwarm" color map is employed to effectively illustrate positive and negative associations in a visually discernible manner.

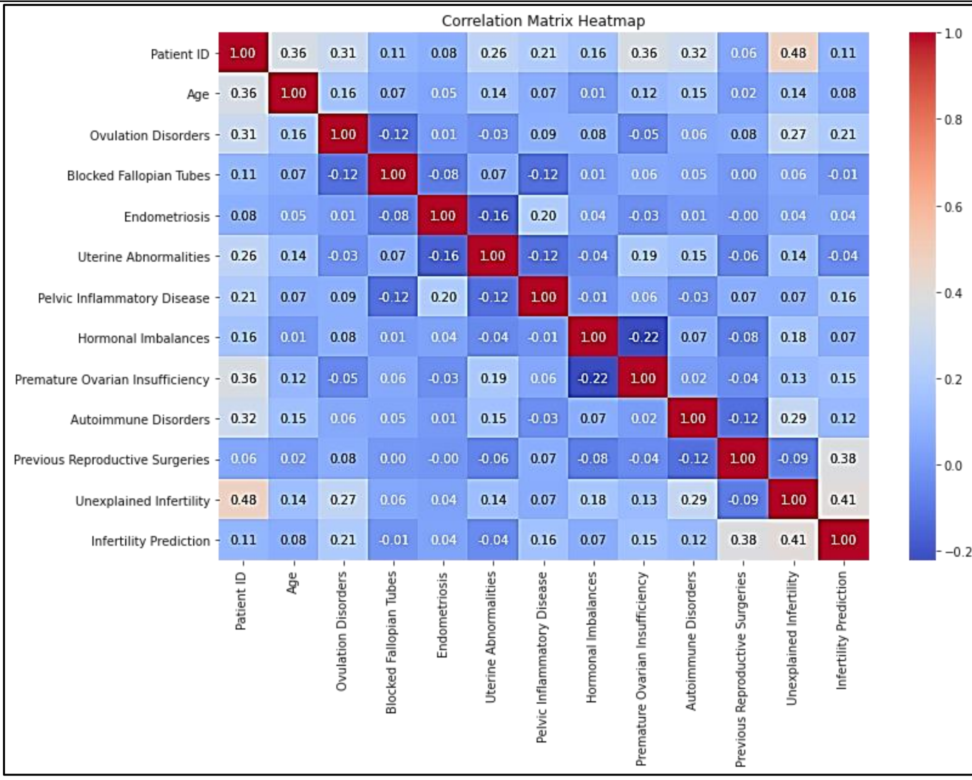

Figure 3: Correlation Matrix Heatmap

Model Building:

This research article primarily focuses on the prediction of female infertility. The dataset is partitioned into two distinct subsets: a training dataset, which encompasses 80% of the data, and a testing dataset, which comprises 20% of the data. The training dataset is employed for the purpose of training a predictive model, while the testing dataset is then utilized to assess the model's performance in order to ascertain its accuracy in making predictions. The Logistic Regression, Naive Bayes, Support Vector Machine (SVM), and Random Forest machine learning methods were employed in our study. The aforementioned algorithms are very suitable for jobs involving binary classification and offer a range of advantages in terms of modeling and prediction. Algorithm selection plays a critical role in healthcare research. In this particular study, we employed Logistic Regression, Naive Bayes, Support Vector Machines (SVM), and Random Forest algorithms to enhance our comprehension and forecasting capabilities about the risks of infertility in women.

Logistic Regression:

Logistic regression is a statistical method for estimating the likelihood that a given instance belongs to one of two classes. It calculates a weighted sum of input features, applies a logistic (sigmoid) function to obtain class probabilities, and optimizes the model's parameters (weights) to minimize the log-loss or cross-entropy loss during training, making it suitable for predicting infertility in women (1 for infertility, 0 for non-infertility) using the provided features.

Initialize weights (β) and learning rate (α).

Repeat until convergence: Calculate predicted probabilities using the logistic **function. -** Update weights using gradient descent.

Return the learned weights (β).

This pseudocode outlines the logistic regression algorithm, which models the probability of infertility (1 for infertility, 0 for non-infertility) based on the provided features.

Pseudocode:
Initialize weights (β) and learning rate (α)

Repeat until convergence:
Calculate predicted probabilities using logistic function
Update weights using gradient descent
Return the learned weights (β)

To perform logistic regression, we initialized the weights (β) and set a learning rate (α). In each iteration, we calculated predicted probabilities using the logistic function and updated the weights/parameters through gradient descent. This iterative process modified the weights to minimize the error between the output and the true value. Upon achieving convergence, the model returned the learned weights, i.e., β. The logistic regression model performed well, attaining an accuracy of 90%, indicating the percentage of correct predictions made by the logistic regression algorithm out of the total number in the sample. **Naïve Bayes:**

The Naive Bayes algorithm is frequently used for classification assignments. It makes predictions based on Bayes' theorem and the assumption of feature independence. By calculating the conditional probabilities of infertility given the attribute values, Naive Bayes can be used to predict infertility risk. The Naive Bayes algorithm, which determines probabilities to forecast infertility risk based on the qualities, is described in this pseudocode.

Pseudocode:

Each time class C:
Determine the previous probability P(C)
For each attribute X_i:
Each time class C:
Calculate P(X_i | C) conditional probability.
For each occurrence (X_1, X_2,..., X_n):
Each time class C:
Using Bayes' theorem, calculate the posterior probability P(C | X_1, X_2,..., X_n).
Assign the instance to the class whose posterior probability is the highest.
The anticipated class labels are returned.

To implement the Naive Bayes algorithm, we started by determining the prior probability P(C) for each class C. For each attribute Xi we then calculated the conditional probability P(Xi|C) for each class C. During classification, for each instance (X1, X2,…,Xn) we used Bayes' theorem to calculate the posterior probability P(C|X1,X2,…,Xn) for each class C. The instance was assigned to the class with the highest posterior probability. The anticipated class labels were then returned. The Naive Bayes model achieved an accuracy of 83%, indicating satisfactory performance in predicting outcomes for the given task, though it may be somewhat less accurate compared to alternative models or methodologies.

Support Vector Machine:

The Support Vector Machine (SVM) is widely recognized as a highly efficient classification algorithm. The objective is to determine the most suitable hyperplane that can effectively separate the data into distinct categories. SVM can be utilized to predict infertility by locating the hyperplane that maximizes the difference between infertile and fertile women.

Initialize Weights (w) and Bias (b) to Zeros: Initialize learning rate (η) and regularization parameter (λ).

Repeat until convergence: For each training example (X, Y): - Calculate the decision boundary: Z = w · X + b. - Update weights and bias based on conditions.

Return the learned weights (w) and bias (b).

This pseudocode outlines the Support Vector Machine (SVM) algorithm, which finds an optimal hyperplane to separate infertility and non-infertility cases.

Pseudocode:

```
Initialize weights (w) and bias (b) to zeros
Initialize learning rate (η) and regularization parameter (λ)
Repeat until convergence:
For each training example (X, Y):
Calculate the decision boundary: Z = w · X + b
Update weights and bias:
If Y * Z <= 1:
w: = w - η * (2 * λ * w - Y * X)
b: = b + η * Y
Else:
w: = w - η * (2 * λ * w)
Return the learned weights (w) and bias (b)
```

To implement the Support Vector Machine (SVM) algorithm, we began by initializing the weights (w) and bias (b) to zeros, and setting the learning rate (η) and regularization parameter (λ). During training, we iterated until convergence, processing each training example (X, Y) to calculate the decision boundary Z=w·X+bZ = w \cdot X + bZ=w·X+b. We then updated the weights and bias based on the value of Y·ZY \cdot ZY·Z. If Y·Z≤1Y \cdot Z \leq 1Y·Z≤1, we adjusted the weights and bias by subtracting η·(2·λ·w−Y·X)\eta \cdot (2 \cdot \lambda \cdot w - Y \cdot X)η·(2·λ·w−Y·X) from the weights and adding η·Y\eta \cdot Yη·Y to the bias. Otherwise, we only updated the weights by subtracting η·(2·λ·w)\eta \cdot (2 \cdot \lambda \cdot w)η·(2·λ·w). This process continued until the algorithm converged. Finally, the learned weights (w) and bias (b) were returned. The SVM algorithm achieved an accuracy of 89%, demonstrating its effectiveness in classifying and predicting the given task with a high level of accuracy on the test data.

Random Forest:

The Random Forest algorithm is an ensemble learning technique that leverages the combination of many decision trees to make predictions. The model exhibits remarkable performance in both classification and regression tasks. The Random Forest algorithm has the capability to effectively capture complex correlations among characteristics and generate precise predictions within the domain of infertility prediction.

Select the quantity of decision trees (N).

Pseudocode:

```
Decide on the Nth decision tree.
Assuming a decision tree i from 1 to N:
sample the training data at random with replacement
For each split, pick a random subset of features.
On the sampled data, create a decision tree.
To forecast something for an instance (X):
Assuming a decision tree i from 1 to N:
Make a forecast utilizing tree trees
Compile the forecasts (for instance, by majority vote for classification).
bring back the last ensemble prediction
```

For every decision tree i between 1 and N: - Sample training data at random with replacement. Select a subset of features at random for each divide. - Construct a decision tree utilizing the sampled data. To make a prediction for an instance (X), perform the following: For every decision tree i between 1 and N: - Determine a forecast using tree i. Compile the forecasts (such as by majority vote for classification). Return the final prediction of the ensemble. This pseudocode describes the Random Forest algorithm, which accurately predicts infertility by combining multiple decision trees.

The Random Forest algorithm operates by first determining the number of decision trees, N, to use. For each tree in the ensemble, it randomly samples the training data with replacement (bootstrap sampling) and selects a subset of features for each split. Each decision tree is constructed using these sampled data and features. During prediction, each tree in the forest independently forecasts an outcome for a given instance. The final prediction is determined by aggregating the individual tree predictions, often through a majority voting mechanism for classification tasks. The Random Forest model demonstrated outstanding performance with an accuracy of 93%, highlighting its effectiveness in accurately predicting and classifying the risk of infertility in women.

Result and Discussion:

The study was conducted on a laptop with an 8th-generation Core i5 processor, an 8350-U processor, and 16 GB of RAM using Jupyter Notebook. The dataset, containing 705 rows and 13 categorical attributes, was preprocessed to remove outliers and enhance model performance. The study utilized Random Forest, Logistic Regression, Nave Bayes, and Support Vector Machine algorithms. We evaluated performance metrics including precision, recall, accuracy, F1 score, and ROC. Eighty percent (80%) of the dataset was allocated for training and twenty percent (20%) for Testing the model. Table 2 demonstrates that Random Forest is the most effective algorithm, with a 93% accuracy and high recall, precision, F1, and AUC scores. The respective AUC scores for Logistic Regression, Support Vector Machine, and Naive Bayes were 0.95, 0.96, 0.95, and 0.87. The respective accuracy rates were 90%, 89%, and 83%.

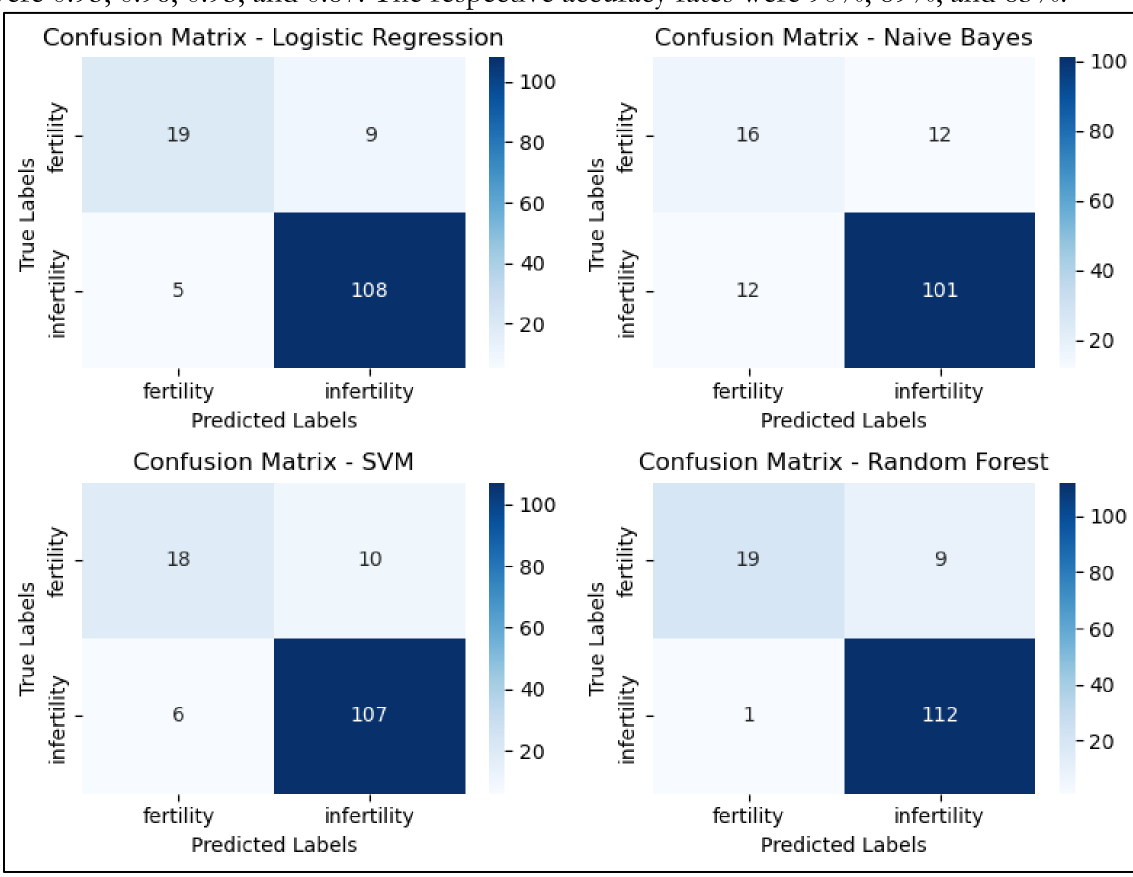

Figure 4: Confusion Matrixes of different Classifiers Used in Model Training

Table 2: Evaluation Matrixes Results of Different Classifiers

Models	Accuracy	Precision (Fertility)	Precision (Infertility)	Recall (Fertility)	Recall (Infertility)	F1-Score (Fertility)	F1-Score (Infertility)	AUC
Logistic Regression	90%	0.79	0.92	0.68	0.96	0.73	0.94	0.96
Support Vector Machine	89%	0.75	0.91	0.64	0.95	0.57	0.89	0.95
Naive Bayes	83%	0.57	0.89	0.57	0.89	0.69	0.93	0.87
Random Forest	93%	0.95	0.93	0.68	0.99	0.79	0.96	0.97

Confusion Matrixes of Machine Learning Classifiers:

Figure 4 shows the confusion matrices of the different classifiers utilized during model training. These confusion matrices are indispensable tools for evaluating model accuracy, revealing how precisely the model predicts outcomes, and evaluating its performance. Each confusion matrix reflects the performance of a unique machine learning model, including Logistic Regression, Naive Bayes, Support Vector Machine (SVM), and Random Forest. To compute these matrices, model predictions (Y_pred_lr, Y_pred_nb, Y_pred_svm, Y_pred_rf) were compared to true labels (Y_test). Using Seaborn's heatmap visualization, the confusion matrices were displayed with annotations demonstrating the true positive, true negative, false positive, and false negative values. The subplots were organized in a 2x2 grid for comparison. This visual representation aids in assessing and comparing the models' abilities to correctly classify instances, as well as identifying areas where each model's classification performance could be improved.

Comparing Machine Learning Algorithm Performance Through Accuracy Scores:

We generated a bar graph comparing the accuracy scores of various machine learning algorithms. We computed the ratings for each algorithm's accuracy and saved them in the "scores" list. The algorithm names are listed on the "algorithms" list. We use Seaborn for plot generation and Matplotlib for customization. The x-axis is titled "Algorithms," while the y-axis is titled "Accuracy Score." This resulting graph provided a fast, visual method for comparing and contrasting the performance of these algorithms based on their respective accuracy scores. A dataset containing 705 instances and 13 attributes was utilized in this implementation. To predict infertility disease in women, four machine learning algorithms, namely Random Forest, Logistic Regression, Support Vector Machine, and Naive Bayes, were employed. Notably, these algorithms demonstrated excellent performance, with respective accuracy rates of 93%, 90%, 89%, and 82%. Random Forest emerged as the most effective algorithm for predicting infertility disease in women among these models, demonstrating its superior predictive abilities in this context.

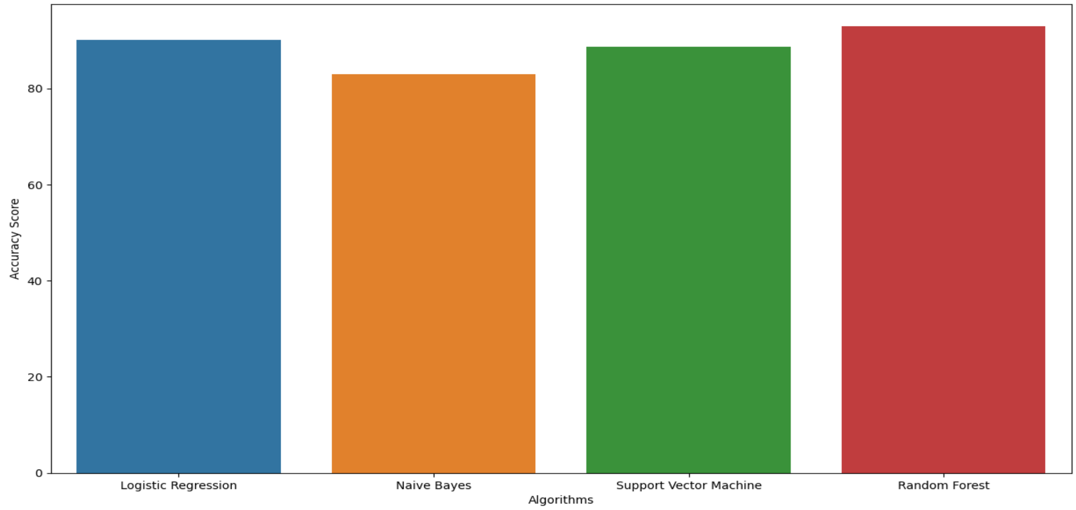

Figure 5: Accuracy Comparison

Table 3, Table 4, Table 5, and Table 6 show the classification results of the machine learning models used in the experimental study of infertility prediction in women.

Table 3: Classification report of Regression model

	Precision	Recall	F1-Score	Support
Fertility	0.79	0.68	0.73	28
Infertility	0.92	0.96	0.94	113
Accuracy			0.90	141
Macro Avg	0.86	0.82	0.83	141
Weighted Avg	0.90	0.90	0.90	141

Table 4: Classification report of Naïve Bayes

	Precision	Recall	F1-Score	Support
Fertility	0.57	0.57	0.57	28
Infertility	0.89	0.89	0.89	113
Accuracy			0.83	141
Macro Avg	0.73	0.73	0.73	141
Weighted Avg	0.83	0.83	0.83	141

Table 5: Classification report of Support Vector Machine

	Precision	Recall	F1-Score	Support
Fertility	0.75	0.64	0.69	28
Infertility	0.91	0.95	0.93	113
Accuracy			0.89	141
Macro Avg	0.83	0.79	0.81	141
Weighted Avg	0.88	0.89	0.88	141

Table 6: Classification Report of Random Forest

	Precision	Recall	F1-Score	Support
Fertility	0.95	0.68	0.79	28
Infertility	0.93	0.99	0.96	113
Accuracy			0.93	141
Macro Avg	0.94	0.83	0.87	141
Weighted Avg	0.93	0.93	0.92	141

Discussion:

The study employed numerous machines learning algorithms, including Logistic Regression, Naive Bayes, Support Vector Machine (SVM), and Random Forest, to predict and comprehend female infertility. The research evaluated the effectiveness of various machine learning algorithms. Among the models we tested, Random Forest's 93% accuracy rate was the highest and most impressive. This result shows that Random Forest does quite well in predicting female infertility with the given variables. Despite Random Forest's impressive 93% accuracy rate, competing algorithms such as Support Vector Machines (SVM), Naive Bayes, and Logistic Regression did somewhat better. However, for producing quick, rough estimates, Random Forest is still a viable option. Support Vector Machine's high accuracy rate of 89% demonstrates its usefulness for predicting infertility. The ability of Support Vector Machines (SVM) to efficiently manage complicated data patterns greatly increased their efficacy. The Logistic Regression method, well-known for its simplicity and success rate, managed an impressive 90% accuracy. Successfully predicting female infertility demonstrated the system's proficiency in binary classification problems. The Naive Bayes Machine has demonstrated its worth with an astonishing 83% accuracy rate. This demonstrates its suitability for the intended purpose of foretelling infertility. The study's results have profound implications for fertility testing and reproductive medicine. The machine learning models have achieved impressive levels of accuracy, making them a vital resource for spotting and alleviating infertility issues among women. Our predicted model can be used in clinical settings, assisting doctors in early diagnosis of infertility and tailoring treatment plans to each patient. This intervention, if used, may lead to a higher quality of care and better outcomes for infertile women. The predictive ability of machine learning in the context of female infertility is demonstrated by this study. The results of this study can be used to better assess and assist couples and individuals who are trying to start a family.

Conclusion:

The current research utilized machine learning algorithms to predict female infertility by using a comprehensive set of medical variables. The Random Forest algorithm shown exceptional efficacy, with a remarkable accuracy rate of 93%. This discovery implies the potential utility of this instrument in the early identification of infertility and the provision of individualized treatment suggestions. While other algorithms such as Logistic Regression, Naive Bayes, and Support Vector Machine also performed well, Random Forest is distinguished by its capacity to identify complex patterns within the data. These findings hold promise for enhancing reproductive healthcare and bolstering assistance for individuals and couples confronting fertility issues.

We can concentrate our future research on refining and expanding the predictive models. Enhanced feature analysis, data enrichment, and deep learning techniques could improve predictive accuracy. In addition, the development of explainability techniques can increase the transparency and credibility of these models among healthcare providers and patients. Integration of these models into clinical practice, validation in the real world, and the development of patient-centric applications are crucial steps toward practical implementation.

Acknowledgment: This work is supported by the IT Lab, Department of Computer Systems Qurtuba University of Science & Information, Technology, Peshawar.

Funding: This research received no external funding.

Conflict of Interest: The authors declare no conflict of interest.

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