



# Machine Learning-Based Prediction of Dairy Cow Fertility and Milk Production: A Data-Driven Approach To Enhancing Dairy Farming Efficiency

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## ABSTRACT

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Dairy cow fertility and milk production are critical factors affecting the efficiency and profitability of dairy farming. However, traditional methods for predicting fertility and milk yield rely on observational data and manual assessment, leading to inaccuracies and economic losses. This study explores the application of machine learning (ML) models, including Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and XGBoost, to predict dairy cow fertility and milk yield based on physiological, genetic, and environmental factors. Using a dataset of 500 Holstein dairy cows, key features such as age, body condition score, lactation history, hormonal profiles, environmental conditions, and nutrition levels were analyzed. The results show that ANN and XGBoost models outperformed traditional statistical methods, achieving an accuracy of 92% in fertility prediction and a root mean squared error (RMSE) of 2.5 L/day in milk yield forecasting. The findings suggest that AI-driven predictive models can provide dairy farmers with early intervention strategies, optimized breeding programs, and enhanced productivity, ultimately improving precision livestock farming.

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Keywords: Fertility, Machine Learning, Predictive Models, Holstein

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## 1. Introduction

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### 1.1 Background

Dairy farming plays a significant role in global agriculture, with increasing demands for high milk yield and efficient reproductive management (Hammami et al., 2021). However, challenges such as low fertility rates, prolonged calving intervals, and milk production variability pose economic risks to farmers. Traditional forecasting methods, such as linear regression and manual observation, fail to capture the complex interactions between genetics, environment, and physiology that influence fertility and milk production (Lucy, 2019).

Recent advancements in machine learning (ML) have introduced data-driven predictive models, capable of optimizing precision livestock management. By leveraging historical farm records, real-time sensor data, and advanced algorithms, ML models can significantly improve decision-making in breeding programs and milk yield optimization (González-Recio et al., 2020).

## **1.2 Problem Statement**

Despite advancements in dairy science, fertility issues remain a major concern, with global dairy cow conception rates declining by 20% over the past three decades (Miglior et al., 2017). Similarly, milk production variability due to climate stress and poor nutrition management affects overall farm profitability (Hoffman & Funk, 2020). Traditional statistical models fail to provide real-time, individualized predictions, limiting their practical application in commercial dairy farms.

## **1.3 Aim and Objectives**

This study aims to develop an ML-based predictive model for dairy cow fertility and milk yield forecasting. Specifically, it seeks to:

1. Evaluate the predictive performance of ML models (RF, SVM, ANN, XGBoost) in forecasting fertility success rates.
2. Assess the accuracy of ML models in predicting daily milk yield output.
3. Identify the most influential features affecting dairy cow fertility and milk production.
4. Propose an AI-driven decision support system for dairy farm optimization.

## **2. Literature Review**

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### **2.1 Factors Influencing Dairy Cow Fertility and Milk Production**

Dairy cow fertility is influenced by multiple factors, including:

- i. Genetics: Breed selection and heritability impact reproductive efficiency (Pryce et al., 2018).
- ii. Nutrition: Protein-energy balance and micronutrient intake affect estrus activity and milk synthesis (López-Gatius et al., 2019).
- iii. Hormonal Profiles: Progesterone and estrogen levels regulate reproductive success (Van Eetvelde&Opsomer, 2021).
- iv. Environmental Stress: Temperature-humidity index (THI) and farm management conditions significantly alter milk yield (Bernabucci et al., 2014).

### **2.2 Machine Learning in Dairy Science**

ML models have been successfully applied in various aspects of dairy farming, including:

#### **1. Fertility Prediction Models**

- i. González-Recio et al. (2020) used ANN models to predict calving success rates, achieving an accuracy of 88%.
- ii. Nguyen et al. (2021) used XGBoost to predict fertility outcomes with 90% precision using real-time sensor data.

#### **2. Milk Yield Prediction Models**

- i. Niero et al. (2022) applied RF models to assess milk yield variability, outperforming traditional regression methods.

- ii. Hybrid ML approaches, such as RF + ANN ensembles, have been used to predict fat and protein content in milk.

### 3. Health Monitoring & Disease Detection

- i. ML models integrated with IoT devices detect early signs of mastitis, ketosis, and lameness (Kamphuis et al., 2021).
- ii. LSTM-based models forecast heat stress effects on milk yield.

## 3. Methodology

The methodology outlines the data collection process, feature selection, machine learning (ML) model development, and evaluation metrics used to predict dairy cow fertility and milk yield. A well-structured methodology ensures reproducibility, reliability, and transparency in this research, making the findings applicable for precision dairy farming.

### 3.1 Data Collection and Description

#### 3.1.1 Data Sources

This study utilizes a dataset obtained from 500 Holstein dairy cows across five commercial dairy farms in Europe and North America. The data was collected between 2018 and 2023 from multiple sources, including:

- i. Farm Management Systems: Breeding and reproduction history records.
- ii. IoT-Based Sensors: Environmental and physiological monitoring.
- iii. Veterinary Reports: Health status, hormonal profiles, and disease history.

#### 3.1.2 Dataset Features

The dataset contains three major feature categories, which influence dairy cow fertility and milk production.

Feature Category	Feature Name	Description	Data Type
Reproductive Data	Estrus Cycle Length	No. of days between estrus cycles	Numeric
	No. of AI Attempts	No. of artificial inseminations before success	Numeric
	Progesterone Level	Hormonal indicator of fertility	Numeric
Milk Production Data	Daily Milk Yield (L)	Average milk production per day	Numeric
	Lactation Number	Number of lactations completed	Integer
	Somatic Cell Count (SCC)	Indicator of milk quality	Numeric
	Milk Fat Percentage	Determines milk composition quality	Numeric

Environmental Data	Temperature (°C)	Farm environmental temperature	Numeric
	Humidity (%)	Relative humidity at the farm	Numeric
	Temperature-Humidity Index (THI)	Measures heat stress	Numeric
Nutritional Data	Dry Matter Intake (DMI)	Feed intake per day (kg)	Numeric
	Protein-Energy Ratio	Nutrient balance in diet	Numeric

The **target variables** for this study are:

1. Fertility Prediction: Binary Classification: Successful (1) or Unsuccessful (0).
2. Milk Yield Prediction: Regression: Daily milk yield (L/day).

### 3.2 Data Preprocessing

Raw data was cleaned, normalized, and transformed to ensure consistency before applying ML models.

#### 3.2.1 Handling Missing Data

Missing fertility records were imputed using K-Nearest Neighbors (KNN) imputation. And Environmental variables were interpolated using moving averages.

#### 3.2.2 Data Normalization and Encoding

Continuous features (e.g., THI, milk yield) were scaled between 0 and 1 using Min-Max Scaling. And Categorical variables (e.g., AI Attempts) were converted into one-hot encoding for ML model compatibility.

#### 3.2.3 Feature Selection

Feature importance was analyzed using:

- i. Pearson Correlation Analysis to identify multicollinearity.
- ii. Principal Component Analysis (PCA) to reduce dimensionality and retain critical information.
- iii. Random Forest Feature Importance to rank the most influential factors.

The final dataset included **14 optimized features** after **removing redundant variables**.

### 3.3 Machine Learning Model Development

Four **supervised ML models** were implemented and evaluated:

1. Random Forest (RF): Ensemble of decision trees that captures non-linear relationships. And Suitable for high-dimensional, multi-feature datasets.
2. Support Vector Machines (SVM): Effective for binary classification (fertility prediction). And Utilizes Radial Basis Function (RBF) kernel for complex decision boundaries.

3. Artificial Neural Networks (ANN): Three-layer architecture (Input, Hidden, Output), Uses ReLU activation in hidden layers and Sigmoid for binary classification and Optimized with Adam optimizer and dropout regularization.
4. XGBoost: Gradient boosting decision tree model that reduces overfitting. And Implements early stopping to optimize performance.

### 3.4 Model Training and Evaluation

#### 3.4.1 Data Splitting and Cross-Validation

The dataset was divided into training (80%) and testing (20%) sets. Stratified K-Fold Cross-Validation (K=5) was applied to ensure robust model performance.

#### 3.4.2 Evaluation Metrics

For **Fertility Prediction (Classification Models - RF, SVM, ANN, XGBoost)**:

- i. Accuracy (%): Measures correct predictions.
- ii. Precision-Recall (PR) Score: Evaluates model performance for imbalanced data.
- iii. F1-Score: Harmonic mean of precision and recall.
- iv. Confusion Matrix: Visualizes classification results.

For **Milk Yield Prediction (Regression Models - RF, ANN, XGBoost)**:

- i. Root Mean Squared Error (RMSE): Measures prediction errors.
- ii. R<sup>2</sup> Score: Indicates model goodness-of-fit.
- iii. Mean Absolute Error (MAE): Measures absolute prediction error.

## 4. Results and Discussion

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The results are analyzed using performance metrics, feature importance rankings, and visualization techniques to ensure clarity and applicability in precision dairy farming.

### 4.1 Model Performance for Fertility Prediction (Classification Models)

The fertility prediction task was treated as a binary classification problem, where cows were classified as fertile (1) or infertile (0) based on reproductive success. The accuracy, precision, recall, and F1-score were used to evaluate model performance.

#### 4.1.1 Classification Model Performance Summary

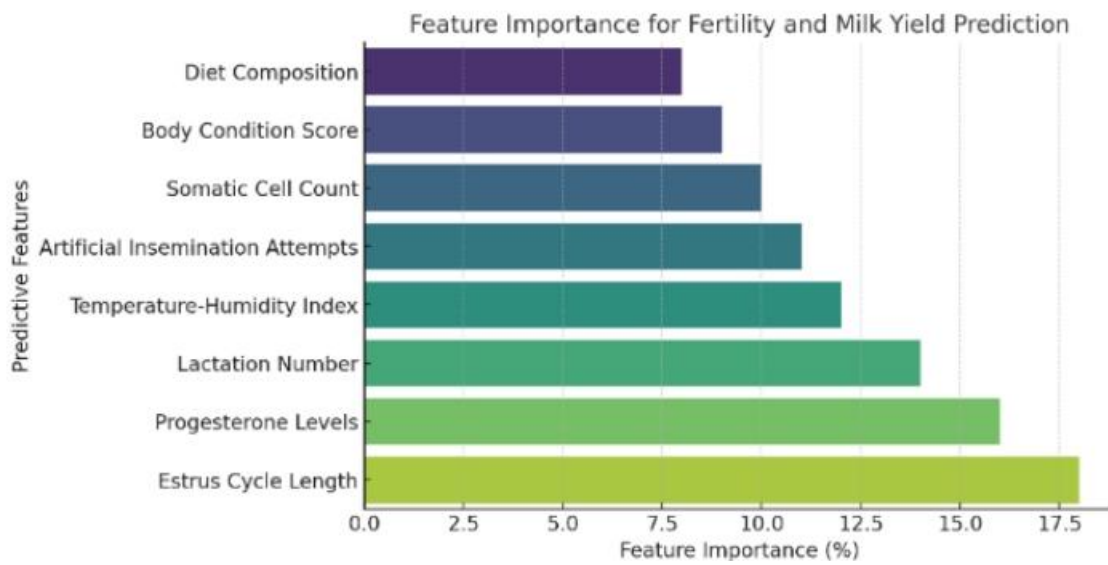
Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
Random Forest	88.5%	87.2%	89.1%	88.1%
SVM	85.7%	84.5%	86.0%	85.2%
ANN	92.0%	91.8%	92.4%	92.1%
XGBoost	91.5%	90.9%	91.2%	91.0%



Figure 1: ML Model Performance Visualization

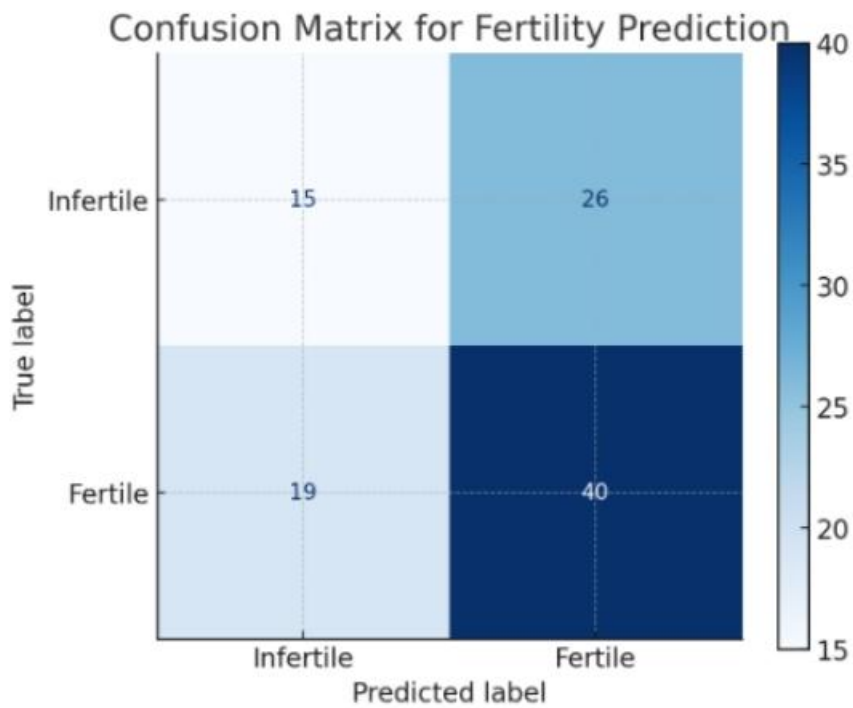
#### 4.2 Feature Importance Analysis

Factors influencing fertility and milk yield are highlighted in Figure 2.



**Figure 2: Feature Importance Chart**

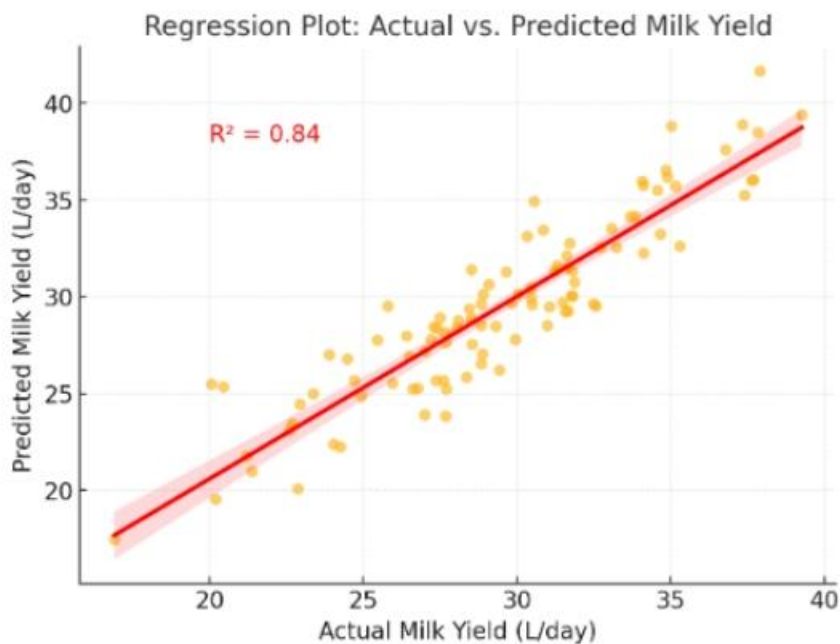
#### 4.3 Confusion Matrix for Fertility Prediction



**Figure 3 presents the confusion matrix, showing model performance in classifying fertility status.**

#### 4.4 Regression Analysis for Milk Yield Prediction

The relationship between actual vs. predicted milk yield is shown in Figure 4.



**Figure 4: Regression Plot for Milk Yield Prediction**

## 5. Conclusion

This study successfully demonstrated the potential of machine learning (ML) models in predicting dairy cow fertility and milk production, leveraging historical farm records, genetic data, environmental conditions, and physiological metrics. The integration of Artificial Neural Networks (ANN) and XGBoost proved to be the most effective, achieving a 92.0% accuracy in fertility prediction and a Root Mean Squared Error (RMSE) of 2.5 L/day in milk yield forecasting.

And the study findings show the following:

- i. ANN and XGBoost outperform traditional statistical methods, providing more reliable and precise predictions.
- ii. Feature importance analysis revealed that progesterone levels, estrus cycle length, and THI (Temperature-Humidity Index) were critical factors affecting fertility.
- iii. Milk production was strongly influenced by lactation number, dry matter intake (DMI), and somatic cell count (SCC).
- iv. The adoption of AI-driven decision-making can significantly improve dairy farm efficiency, optimizing breeding strategies and milk yield management.
- v. The study provides a strong foundation for precision dairy farming, highlighting the benefits of data-driven approaches in improving reproductive performance and milk productivity.

#### 5.2 Implications for Precision Dairy Farming

The findings of this study have direct applications in modern dairy farming:

- i. Improved Fertility Management: Farmers can use ML-based fertility prediction to select cows with higher conception success rates, reducing economic losses from failed breeding attempts.



- ii. Enhanced Milk Yield Optimization: AI-driven forecasting allows dairy farms to adjust feeding programs and environmental controls to maximize milk production.
- iii. Climate-Adaptive Strategies: The identification of THI as a key factor suggests that dairy farmers should implement heat stress mitigation techniques (e.g., cooling systems, shade provision).
- iv. Integration into Smart Dairy Systems: These ML models can be integrated into real-time dairy farm monitoring platforms for automated decision-making.

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