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Optimizing Snail Farming: Predictive Modelling of Terrestrial Snail Output Using Machine Learning

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ABSTRACT

Heliciculture, the cultivation of edible land snails, is gaining prominence as a sustainable and economically viable agricultural sector. Despite this growth, productivity in snail farming remains inconsistent due to variable environmental conditions and empirical management practices. This study applies machine learning (ML) techniques for the first time to predict production outcomes in *Cornu aspersum maximum* farms across Greece. Data were collected from 30 operational farms using structured questionnaires, covering biological, environmental, and management-related variables. A suite of supervised ML algorithms, Support Vector Machine (SVM), Neural Network, Stochastic Gradient Descent, and Linear Regression, were trained and evaluated using stratified 5-fold cross-validation. SVM was the most accurate model, achieving 85% predictive accuracy. SHAP (SHapley Additive exPlanations) analysis identified snail density, feed quantity, and mortality rate as the three most critical variables influencing production output. Additionally, hierarchical clustering distinguished two farm clusters with distinct performance patterns, suggesting divergent production strategies. These results demonstrate the potential of ML to inform precision management in heliciculture. By identifying key predictors of productivity, this study provides a decision-support framework for optimizing farm inputs and enhancing operational sustainability. Results highlight the value of digital tools in transforming traditional snail farming into a data-driven and efficient system.

Keywords: Heliciculture; *Cornu aspersum maximum*; Machine Learning; Predictive Modeling; Snail Farming; Production Optimization

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ARTICLE INFO
Received: 30 July 2025 | Revised: 2 December 2025 | Accepted: 10 December 2025 | Published Online: 17 December 2025
DOI: https://doi.org/10.55121/nc.v5i1.643

CITATION
Apostolou, K., Hatziioannou, M., Klaoudatos, D., 2026. Optimizing Snail Farming: Predictive Modelling of Terrestrial Snail Output Using Machine Learning. New Countryside. 5(1): 69–88. DOI: https://doi.org/10.55121/nc.v5i1.643

1. Introduction

1.1. Background and Importance of Heliciculture

Snail farming, or heliciculture, refers to the breeding of edible land snails for food, cosmetic, and medicinal purposes [1,2]. It represents a sustainable and profitable alternative in agriculture which is gaining popularity as an environmentally friendly alternative to traditional livestock. It requires less space and capital investment, while emitting fewer greenhouse gases [3,4]. Additionally, snail farming offers potentially, high economic returns [5]. Today, snail farms are established in many countries (France, Italy, China, Australia, Mediterranean region) with extensive and intensive farming methods developed [6–8], where production and export of large quantities of snails takes place.

Globally, terrestrial gastropods, including snails, are considered a valuable alternative protein source for a rapidly growing global population, projected to reach nine billion by 2050 [9]. In Europe, annual consumption of edible snails exceeds 100,000 tons, and total imports increased by 49% between 1995 and 2010 [10,11]. The demand for edible snails is growing globally, particularly in Europe and Africa, so in 2018, the total production reached 750,000 tons [12]. In 2021, the European Union imported up to 15,000,000 kg of land snails (HS 030760: “snails other than sea snails”) [13]. Recent scientific analyses suggest that the global market for edible snails worth €1 billion and corresponds to 300,000 tones, implying that imports continue to play a critical role in filling gaps left by domestic production [14]. Also, land snails are a product of high nutritional value and a source for the production of specialty products (snail caviar, mucus) of high commercial value [15]. In recent years, the use of snail extract in dermatology has expanded, as it has demonstrated therapeutic, sedative, and anti-aging properties [1,2,16]. The most common species farmed are *Cornu aspersum aspersum* and *Cornu aspersum maximum* [1,3,17,18] due to their high productivity, their favorable growth characteristics, adaptability, and market acceptance.

Despite growing interest, production optimization remains inconsistent due to environmental and operational variability [17]. Challenges include feed costs, regulations, and socio-cultural barriers [2,19]. Climate factors like humidity and rainfall negatively impact technical efficiency of snail farms in Nigeria [20]. In Spain, challenges include standardization, and competition, though proper investment and support could boost the industry’s economic contribution [19]. Heliciculture in various countries faces obstacles such as limited industrial production capacity and insufficient scientific research [21]. Also, snail farming faces challenges such as parasitic infections, which can threaten farm viability [22,23].

As the increasing global demand for alternative protein sources and ongoing research in pharmaceutical and cosmetic industries grow, heliciculture is emerging as a promising part of sustainable agriculture [2]. Further research and development are essential to fully realize its potential into sustainable agricultural systems [21,24].

1.2. The Role of Machine Learning in Enhancing Animal Farming Efficiency

Machine learning (ML) is revolutionizing agriculture and livestock management, offering innovative solutions for enhancing productivity, animal welfare and sustainability. ML algorithms are employed across various agricultural sectors such as crop, livestock, soil, and water management [25,26].

The adoption of innovative technologies in agriculture has helped to make farming more industrial leading to higher production, but also more sustainable [27]. Also, technology tools (ML and AI), optimized processes, improve land use and crop selection [28,29]. In total, in crop management, ML techniques are applied for yield prediction, disease detection, pest control, resource efficiency and quality assessment [28,30,31]. Also, AI and ML models, show that they can reduce water waste as well as chemical use by 41% and 33% [32].

In aquaculture, ML can be integrated to predict fertility patterns, diagnose eating disorders [30], help to feed optimization and assist in transforming it into a sustainable production system [33–35]. Mohale et al. [36] noted that thanks to new applications, aquaculture triplicate their production, while Utku and Kutlu [37] highlight that these applications significantly improve efficiency and reduce cost. Machine learning (ML) is increasingly transforming aquaculture by enabling more precise, data-driven management across production systems. Recent studies demonstrate that ML techniques, particularly convolutional neural networks and hybrid deep learning models, significantly improve the early detection of fish diseases, often surpassing human visual inspection in accuracy and speed [38,39]. Other work highlights their capacity to optimize feeding strategies, with predictive models reducing feed conversion ratios and lowering production costs in experimental recirculating aquaculture systems [40,41]. In addition, ML algorithms have been successfully applied to biomass estimation, automated counting, and water quality forecasting, supporting more efficient resource use and timely corrective interventions [33,42]. Collectively, this body of research indicates that ML has a measurable impact on aquaculture sustainability, enhancing productivity while reducing waste and environmental pressures.

In livestock systems, ML aids in monitoring animal welfare, predicting fertility patterns, and diagnosing eating disorders using data from collar sensors [30]. Also, ML applications, combined with sensors and imaging, are transforming livestock management by detecting diseases, monitoring behaviors, forecasting production yields, and managing feeding schedules [26].

In cattle farming, technology applications such as ML have emerged as promising tools in dairy farm management, improving the farming process [43]. These technologies include real-time health monitoring, early disease detection, and optimization of feeding efficiency [44,45]. ML algorithms also have been applied to predict milk yield and quality assessment [46], analyze animal behavior and improve overall farm management [31,47,48]. These techniques can process large datasets from sensors and routine operations, providing valuable insights for farmer decision support [31,44]. Despite the obstacles, ML is expected to play a crucial role in future dairy farm management, particularly in areas like welfare monitoring and environmental impact mitigation [49].

In poultry industry, IoT and ML technologies enable environmental monitoring, early identification of diseased chickens, animal growth and precision resource optimization [50–53]. Machine learning (ML) has significantly advanced the poultry sector by enhancing disease detection, environmental control, and overall farm management enabling timely interventions [54,55]. ML approaches have been applied to analyze big data streams from sensors and digital technologies, facilitating precision feeding and automation in poultry production systems [56]. These advancements contribute to increased efficiency, improved animal welfare, and enhanced sustainability in poultry farming [57].

Machine learning (ML) and artificial intelligence (AI) have significantly transformed sheep farming, enhancing efficiency and productivity. AI-powered systems enable remote monitoring of livestock health through wearable devices tracking vital signs and behavior [58]. ML techniques have been applied to predict sheep body composition, estimate body weight, sheep susceptibility to parasites or diseases and even adult wool growth and quality [59–61]. Additionally, deep learning models have achieved 95.8% accuracy in automatic sheep breed classification using on-farm image data, potentially assisting farmers in breed identification and cost management [62,63].

These advancements contribute to sustainable practices by minimizing waste and reducing the ecological footprint of livestock farming [45].

1.3. Absence of Predictive Modelling in Snail Farming

In contrast, despite helicicultures' commercial expansion, there is a lack of ML application in heliciculture, indicating potential for future research and development in this area. Snail farmers rely mostly on empirical practices to regulate critical factors such as snail density, feed, mortality, climatic conditions in closed farming types. Consequently, production efficiency and profitability often vary widely, even among similar farming systems. To date, no scientific studies have dealt with predictive modeling and Machine learning, to systematically evaluate and optimize snail production.

1.4. Aim of the Study

This paper focuses on identifying the key variables that influence total production output in terrestrial snail farms, raising *Cornu aspersum maximum*, through the application of predictive modeling techniques. To achieve this, data were collected from 30 operational snail farms across different regions. Beyond variable identification, the research aims to explore for the first time how machine learning methods can contribute to increased productivity and efficiency in heliciculture.

2. Materials and Methods

2.1. Selection of Snail Farms

The selection of snail farms was necessary due to the relatively small number of operational farms in Greece. Efforts were made to ensure that the selected farms met two basic criteria:

- Farming System
- Geographical Location

Figure 1 presents the distribution of the 30 participating farms, all of which breed *Cornu aspersum maximum* snails for human consumption. There were located across seven regions (Central and Western Macedonia, Thessaly, Thrace, Western Greece, North Aegean, Attica) mainly on the Greek mainland. Snail farming units mainly are active from April to November, a period in which Greece experiences warm temperatures, prolonged sunshine, and limited rainfall (Hellenic National Meteorological Service).

The relationship between farming type, altitude and climatic conditions for each farm is shown in **Figure 2**. As shown in **Figure 2**, most net-covered greenhouses, elevated sections and mixed system farms are in areas with lower altitude and higher average temperature.

On the contrary, in open fields in Greece demonstrate a more balanced distribution in terms of altitude and average temperature. Specifically, 45% of these farms are in areas above 400 m, while 55% have mean temperature below average.

Data was collected using a structured questionnaire administered through in-person interviews with snail farmers. Each interview lasted approximately 2 to 3 h and included a combination of open-ended and closed questions. Data was collected on farm management practices, technical infrastructure, and the breeding process. The design of the questionnaire was developed using previous relevant surveys as reference models [64–68], which were adapted to align with the objectives and specific context of this research.

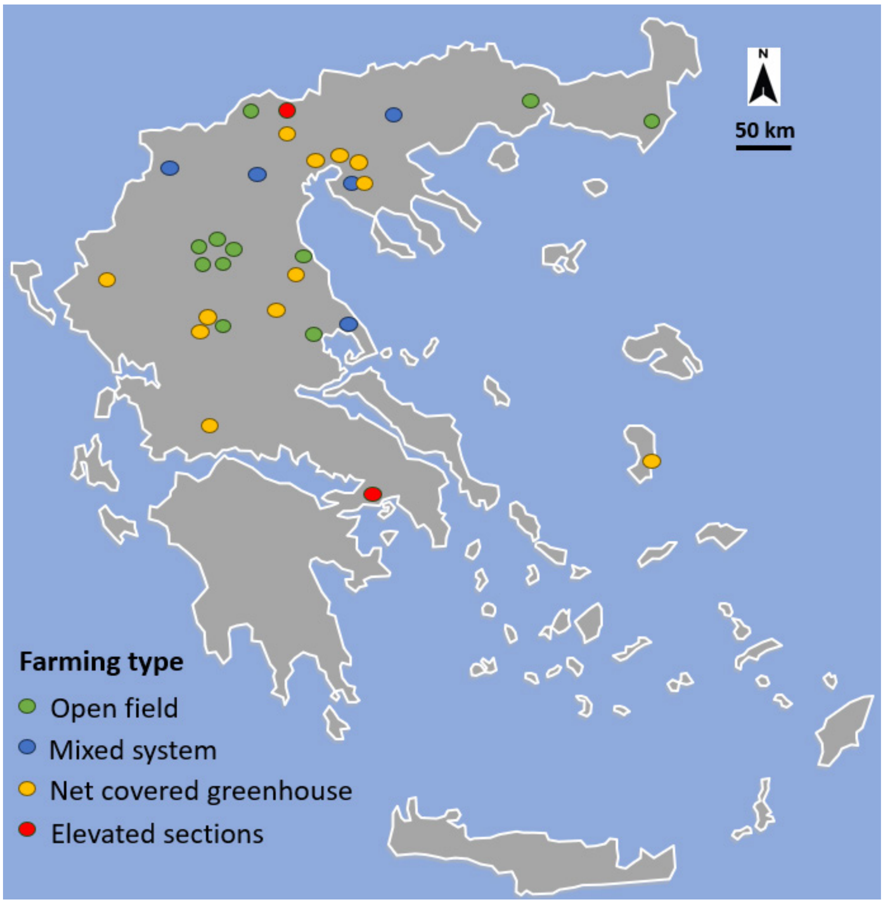

Figure 1. Map of Greece and location of snail farms studied (color indicate farming type).

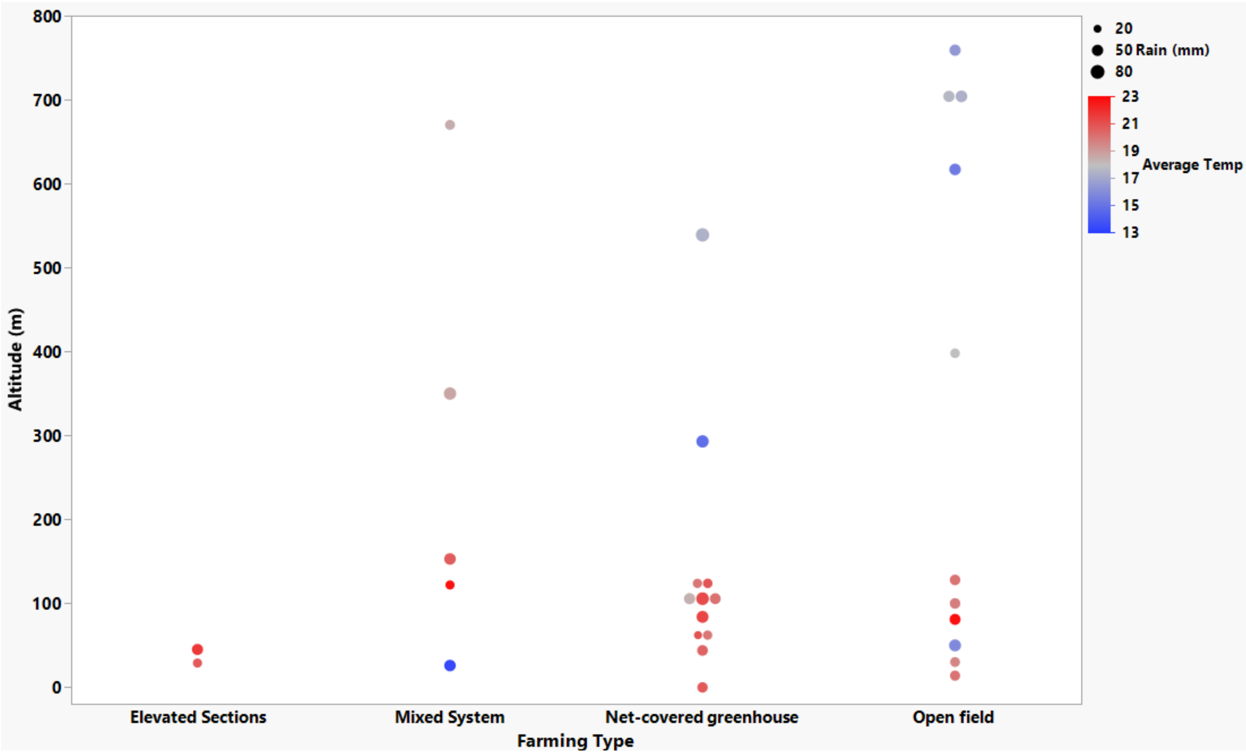

Figure 2. Altitude and climatic conditions of snail farms during research (each point represents one snail farm; size of points indicates amount of rainfall and color the average temperature).

2.2. Data Description

The data collected (**Table 1**) included five (5) main categories, the most important of which: Livestock (Density, Number of Snails/kg, Growth rate, Mortality rate), Total Production, Land (Altitude, Farming area), Management and Nutrition (Duration of operation, Feed quantity), Climatic conditions (Temperature, Rainfall). Finally, questions about Farming type, Equipment, and Facilities were included in the survey.

Table 1. Description of Variables Collected from 30 Snail Farms.

Variable	Description	Data Type
Farming Type	Elevated Section – Net-covered greenhouse – Mixed system – Open field	Categorical
Density (snails/m^2)	Biomass of snails per square meter of farm area.	Numerical
Mortality (%)	Total number of dead snails × 100/Initial number of snails	Numerical
Number of Snails/kg	Average number of marketable snails per kg	Numerical
Altitude (m)	Altitude of the farm	Numerical
Average Temp (°C)	Mean temperature during the operation of snail farm	Numerical
Rain (mm)	Average rainfall near the farm	Numerical
Farming Area (m^2)	Total area of snail farm	Numerical
Production (kg/m^2)	Total snail production per m^2 of each farm at the end of its operating period (target variable).	Numerical
Growth Rate (g/day/snail)	Mean weight gain per snail per day − Growth rate = Final weight – Initial weight/Breeding period (days)	Numerical
Duration of Operation (months)	Number of months during which the snail farm was operating	Numerical
Feed Quantity (kg)	Total amount of feed used during the farm operation	Numerical
Facilities Score (0–10)	Quantity of facilities in farms, rated from 0 to 5	Ordinal
Equipment Score (0–10)	Quantity of equipment, rated from 0 to 5	Ordinal
Extensive–Intensive Farming	Farming type and Management style on a scale from 1 (extensive) to 5 (intensive)	Ordinal

2.3. Hierarchical Clustering

Hierarchical clustering was employed as an unsupervised learning method used to identify natural groupings in a dataset based on similarity or distance between observations. In this analysis, the Ward method was applied, which is an agglomerative clustering technique that minimizes the total within-cluster variance at each step of the algorithm. The method begins with each observation as a separate cluster and iteratively merges the two clusters that lead to the smallest increase in the total within-cluster sum of squares [69]. This approach is particularly effective in producing compact and spherical clusters and is sensitive to outliers and noise, which is why it is often used in ecological and biological studies. Prior to clustering, standardization of variables (mortality, snail density, and feed quantity) was performed to ensure that each variable contributed equally to the distance calculations regardless of its original scale [70]. The resulting dendrogram allows for the visual inspection of cluster structure and the identification of natural groupings within the data. The number of clusters can be selected based on the height of the branches or through evaluation of distance metrics or validation indices.

2.4. Machine Learning

Predictive analysis with supervised ML algorithms was applied to determine the principal contributing components influencing total production. A second-degree stepwise regression, using the minimum Bayesian Information Criterion (BIC) as the stopping rule, was fitted to identify the factors from the 15 potential influences on total snail production (**Table 2**) that had significant effects, along with their relative importance [71]. Multicollinearity was assessed using the Variance Inflation Factor (VIF) (VIF < 5) [72].

Table 2. Main variables recorded for each farming type (Altitude, climatic conditions, production, growth rate and mortality in snail farms during the study).

	Farming Type	N	Mean	Median	Minimum	Maximum
Altitude (m)	Elevated Sections	2	36.0 ± 9.9	36	29	43
	Mixed System	5	264.2 ± 255.6	153	26	670
	Net-covered greenhouse	12	135.3 ± 145.4	104.5	0	539
	Open field	11	324.9 ± 313.2	128	14	759
Average Temp	Elevated Sections	2	21.3 ± 0.6	21.29	20.83	21.77
	Mixed System	5	18.9 ± 3.5	18.71	13.42	22.88
	Net-covered greenhouse	12	19.7 ± 1.9	20.35	14.81	21.41
	Open field	11	18.5 ± 2.6	18.04	15.31	22.87
Rain (mm)	Elevated Sections	2	39.2 ± 12.9	39.20	30.06	48.33
	Mixed System	5	46.8 ± 13.3	52.27	29.60	62.84
	Net-covered greenhouse	12	46.3 ± 16.2	44.62	21.80	75.07
	Open field	11	45.8 ± 7.8	47.11	33.40	56.62
Production (kg/m^2)	Elevated Sections	2	2.3 ± 1.1	2.25	1.50	3.00
	Mixed System	5	0.9 ± 0.5	1.00	0.20	1.50
	Net-covered greenhouse	12	1.7 ± 0.9	1.50	0.38	4.40
	Open field	11	0.4 ± 0.3	0.30	0.10	1.00
Growth rate (gr/day/snail)	Elevated Sections	2	0.15 ± 0.04	0.153	0.124	0.181
	Mixed System	5	0.14 ± 0.05	0.154	0.084	0.193
	Net-covered greenhouse	12	0.1 ± 0.03	0.085	0.060	0.167
	Open field	11	0.09 ± 0.04	0.094	0.059	0.167
Mortality	Elevated Sections	2	15 ± 7	15	10	20
	Mixed System	5	25 ± 16	20	5	50
	Net-covered greenhouse	12	23.5 ± 18	20	5	70
	Open field	11	30.9 ± 10	30	5	45

The Pearson correlation coefficient (PCC) was additionally used to evaluate the strength of linear associations among the various environmental factors [73], calculated as (Equation (1)):

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (1)$$

Where:

n is the sample size,

Σ is the summation of all values.

Sample-size to Feature-size Ratio (SFR) [74] was also employed to assess the sufficiency of the data used to answer the defined research question (total snail production) calculated as (Equation (2)):

$$\text{SFR} = \frac{n}{p} \quad (2)$$

Where:

n is the number of samples, observations, or data points,

p is the number of features, variables, predictors, or dimensions.

Following data collection, the dataset was partitioned into training and testing subsets with a 70:30 ratio. The models were subsequently trained and optimized for performance. No preprocessing was performed prior to analysis. Model evaluation and comparison were conducted using stratified 5-fold cross-validation, with performance assessed via key metrics. The evaluated models included Stochastic Gradient Descent (SGD), Support Vector Machine (SVM), Neural Network, and Linear Regression (**Figure 3**).

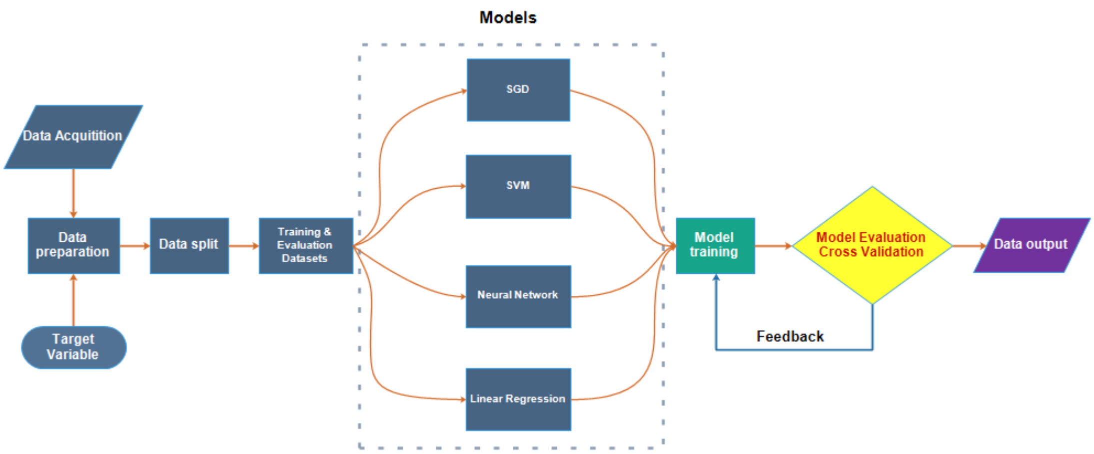

Figure 3. Workflow illustrating the predictive analysis process with supervised machine learning algorithms.

Rectangles indicate data processing tasks, ovals represent starting points, diamonds designate decision nodes, and parallelograms show input and output operations. Color-coding highlights process categories: blue signifies data-related activities, green marks model training and development, yellow identifies evaluation and testing steps, and purple corresponds to deployment and monitoring phases.

2.5. Description of ML Algorithms

2.5.1. Stochastic Gradient Descent (SGD)

Stochastic Gradient Descent (SGD) is a core optimization technique in machine learning for efficient model training. It iteratively updates model parameters using either a single randomly selected sample or a small batch, instead of the entire dataset [75]. The inherent randomness in SGD introduces variability in parameter updates, which can accelerate convergence and improve generalization. By incrementally adjusting parameters to reduce the loss function, SGD facilitates effective training of complex models. However, its stochastic behavior necessitates careful tuning of the learning rate and other hyperparameters to ensure stable convergence to an optimal solution [76].

2.5.2. Support Vector Machine (SVM)

SVM is a supervised machine learning algorithm primarily utilized for classification tasks, as it assigns labels to input data by recognizing patterns learned from the training examples [77,78]. The decision boundary in an SVM is determined by support vectors, the data points nearest to the separating hyperplane. SVM's effectiveness lies in its ability to deliver high accuracy and robust generalizability in complex, high-dimensional datasets, such as those common in medical research, by skillfully controlling model complexity and reducing training errors [78].

2.5.3. Neural Network

Neural networks are computational systems modeled after the structure and functionality of the human brain, consisting of interconnected nodes that process input data into outputs through weighted connections and activation functions [79]. In machine learning, they perform exceptionally well in tasks such as classification, regression, and pattern recognition by learning patterns directly from data, without requiring hand-crafted rules [80].

2.5.4. Linear Regression

Linear regression serves as a fundamental machine learning technique for regression problems, forecasting a continuous target variable from one or more predictor features. It posits a linear relationship between the independent and dependent variables, represented by a straight line [81]. The method adjusts its coefficients to reduce the mean squared error between predictions and observed values in the training set. Owing to its straightforwardness, interpretability, and suitability for linearly related data, linear regression finds extensive use in disciplines such as economics, biology, and social sciences [72].

2.6. Assessment of Model Performance

Model performance was evaluated using five metrics: Mean Square Error (MSE), the average of squared differences between predicted and actual values; Root Mean Square Error (RMSE), which measures the magnitude of prediction errors; Mean Absolute Error (MAE), the average of absolute differences between predictions and observations; Mean Absolute Percentage Error (MAPE), which indicates average error as a percentage of actual values; and the Coefficient of Determination (R^2), which shows the proportion of variance in the dependent variable accounted for by the model.

2.6.1. Mean Square Error (MSE)

MSE, or Mean Squared Error, quantifies a model's accuracy by calculating the average of the squared differences between the observed values and the model's predicted values. Mathematically, it is expressed as (Equation (3)) [72]:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{yi})^2 \tag{3}$$

Where: n refers to the number of observations, yi signifies the actual values and $\hat{yi}$ denotes the predicted values. A lower MSE value suggests the model fits the data more accurately, as it means the predictions are closer to the true values.

2.6.2. Root Mean Square Error (RMSE)

RMSE evaluates model accuracy by expressing errors in the same units as the original data, like MSE. RMSE is determined by taking the square root of the average squared differences between actual and predicted values. It is expressed as (Equation (4)) [82]:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{yi})^2} \tag{4}$$

Where: n is the number of observations, yi denotes the actual values and $\hat{yi}$ represents the predicted values.

RMSE is widely used because it provides an intuitive measure of a model's error size, simplifying the process of understanding and comparing model performance. Lower RMSE values indicate a better fit to the data.

2.6.3. Mean Absolute Error (MAE)

MAE measures model accuracy by averaging the absolute differences between actual and predicted values. Unlike MSE and RMSE, which square these differences, MAE is less sensitive to outliers. It is expressed as (Equation (5)) [82]:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|yi - \hat{yi}| \tag{5}$$

Where: n is the number of observations, yi denotes the actual values and $\hat{yi}$ represents the predicted values.

MAE provides a straightforward measure of the average error size, helping to gauge how many predictions differ from actual values on average. Lower MAE values suggest a better model fit with the data.

2.6.4. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) evaluates model accuracy by computing the average absolute percentage difference between actual and predicted values. This metric expresses error as a percentage, making it easier to interpret the size of the error in relation to the true values. It is defined mathematically as (Equation (6)) [82]:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{yi-\hat{yi}}{yi}\right| \times 100 \quad (6)$$

Where: n is the number of observations, yi represents the actual values and $\hat{yi}$ represents the predicted values.

MAPE is useful for evaluating forecasting accuracy across varied datasets by expressing errors as percentages. Smaller MAPE values indicate a better model fit, with values near 0% reflecting greater accuracy.

2.6.5. Coefficient of Determination (R2)

The coefficient of determination is a statistical measure that assesses how well a regression model describes the observed data. It indicates the proportion of variance in the dependent variable explained by the independent variables, with values between 0 and 1, higher values reflect a stronger model fit. It is expressed as (Equation (7)) [72]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(yi-\hat{yi})^2}{\sum_{i=1}^{n}(yi-\bar{y})^2} \quad (7)$$

Where: n is the number of observations, yi denotes the actual values and $\hat{yi}$ represents the predicted values and is the mean of the actual values.

An R^2 value of 1 means the regression model fully predicts the dependent variable, whereas an R^2 value of 0 shows the model accounts for none of the dependent variable's variance.

3. Results

3.1. Farm Prevailing Conditions

A summary of the prevailing conditions of the farms surveyed including altitude, climatic characteristics, production and growth rate for each farming type is shown in **Table 2**.

Temperature and rainfall values were obtained from local meteorological stations situated near each snail farm. The highest recorded mean temperature was 22.88 °C in Thessaly, while the lowest was 13.42 °C, recorded in Central Macedonia (Serres).

Average rainfall across all farms was 44.59 mm. The highest mean rainfall was 75.07 mm, recorded in Western Greece (Ioannina), while the lowest was just 21.8 mm, observed on the island of Chios (**Table 2**).

The average altitude at which the snail farms are located is 219 m, with an average temperature of 19 °C and mean annual rainfall exceeding 45 mm. Snail farms in Greece are generally classified as semi-intensive, with an average intensity score of 2.7. These farms are typically characterized by limited facilities but adequate equipment.

In Greece, the typical farm size for snail production is around 3700 m^2, and farms generally operate for approximately eight months per year. The mean farming density is 114.7 snails/m^2, with a maximum of 300 snails/m^2 recorded in a net-covered greenhouse and a minimum of 20 snails/m^2 in open-field systems. As indicated in **Table 2**, the mortality rate averages 26%, while the annual total production per farm area exceeds 1 kg/m^2.

3.2. Hierarchical Clustering

A hierarchical clustering dendrogram visualized the grouping of snail production units (kg/m^2) based on the three key variables identified: mortality, snail density, and feed quantity, each represented using a heatmap with a distinct color scale (green to red for low to high values) (**Figure 4**).

The heatmap displays standardized values for three key parameters: mortality (%), snail density (snails/m^2), and feed quantity (kg). The dashed red vertical line indicates the selected cut-off level for defining clusters, resulting in two major clusters.

The heatmap revealed clear variation across observations, with red indicating higher values (e.g., higher mortality, density, or feed input) and blue/green indicating lower values. Based on the dendrogram and the vertical red dashed line indicating the selected clustering threshold, two major clusters emerged. The lower cluster corresponded to low mortality, moderate feed input, and snail densities in the green-to-blue range, suggesting more sustainable or efficient conditions. In contrast, the upper cluster comprises units with higher mortality, higher snail densities, and greater feed input (reflected in red/orange hues), implying potential overstocking or overfeeding issues. This clustering revealed two distinct production strategies or outcomes in the dataset, revealing distinct production patterns, which may guide targeted management practices.

The distance metric curve in the bottom panel (**Figure 4**) depicted a marked inflection point suggesting the appropriate level for cluster division. These clusters likely reflect different production strategies or environmental conditions, with one group showing lower mortality and moderate inputs, and the other characterized by higher mortality, density, and feed input.

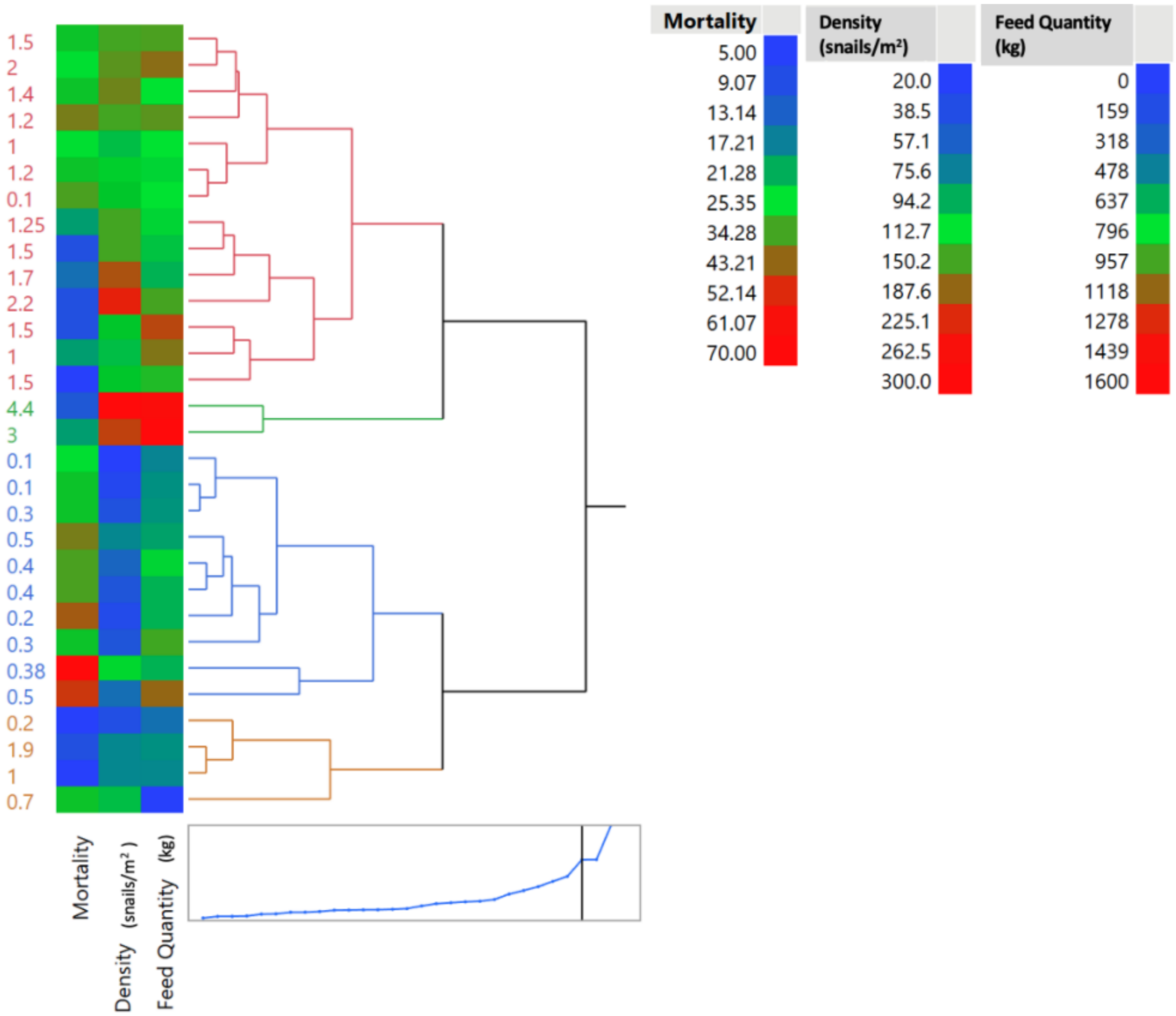

Figure 4. Hierarchical clustering of *Cornu aspersum maximum* production, performed using the Ward method with standardized variables.

3.3. Model Performance

The performance of the models was evaluated using five distinct metrics, MSE, RMSE, MAE, MAPE, and R^2, to ensure a comprehensive comparison, as each metric offers unique advantages and limitations (**Figure 5**). For instance, while MSE and RMSE are more sensitive to outliers, MAE and MAPE provide robust measures of average error. Among these metrics, lower values for MSE, RMSE, MAE, and MAPE, along with a higher R^2 score, signify superior model performance. This multi-metric approach allowed for a balanced assessment of predictive accuracy and error tolerance across the tested models.

Based on metric results (**Figure 5**) SVM demonstrated the best overall accuracy, with the lowest MSE (0.134), RMSE (0.366), and MAE (0.265), as well as the highest R^2 score (0.849), indicating strong predictive power and minimal errors. Linear Regression followed, with moderate performance, while SGD and Neural Network showed slightly higher errors and lower R^2 scores, suggesting less accuracy. Notably, SGD had the lowest MAPE (0.592), implying better relative error performance despite its other metrics being weaker. Overall, SVM outperformed the other models across most metrics, making it the most accurate choice for this task.

The SHAP (SHapley Additive exPlanations) method was applied to demonstrate the contribution and importance of each feature to the model's predictions (**Figure 6**). SHAP values quantify the effect of individual features on the model's output [83]. According to SHAP analysis, snail density emerged as the most influential feature, followed by feed quantity and mortality. Positive SHAP values (to the right of the center) indicate feature values that increase the likelihood of predicting the target class, whereas negative values (to the left) suggest a reduction in that likelihood [84]. Feature values are visualized with a color scale, where red represents higher values and blue denotes lower values; the gradient reflects the full range of each feature's values in the dataset.

SVM model demonstrated high accuracy (85%) in forecasting *Cornu aspersum maximum* production, with performance metrics indicating reliable predictive capability across diverse farming conditions.

All three of these factors are critical to the success of snail farming. High farming density can increase the risk of parasite transmission within the snail population. An increase in mortality rate leads to reduced production, and if not carefully monitored, this reduction can become significant. Increased mortality not only reduces the number of marketable snails, but also increases production costs, reducing feed conversion efficiency and prolonging the production cycle. Such losses reduce the overall profitability of the farm, as fixed operating costs are spread over a smaller yield. Lastly, feed quantity represents the largest annual operating cost for snail farms. Despite the cost, regular feeding every 2–3 days is essential to ensure growth, optimal breeding performance and high total production.

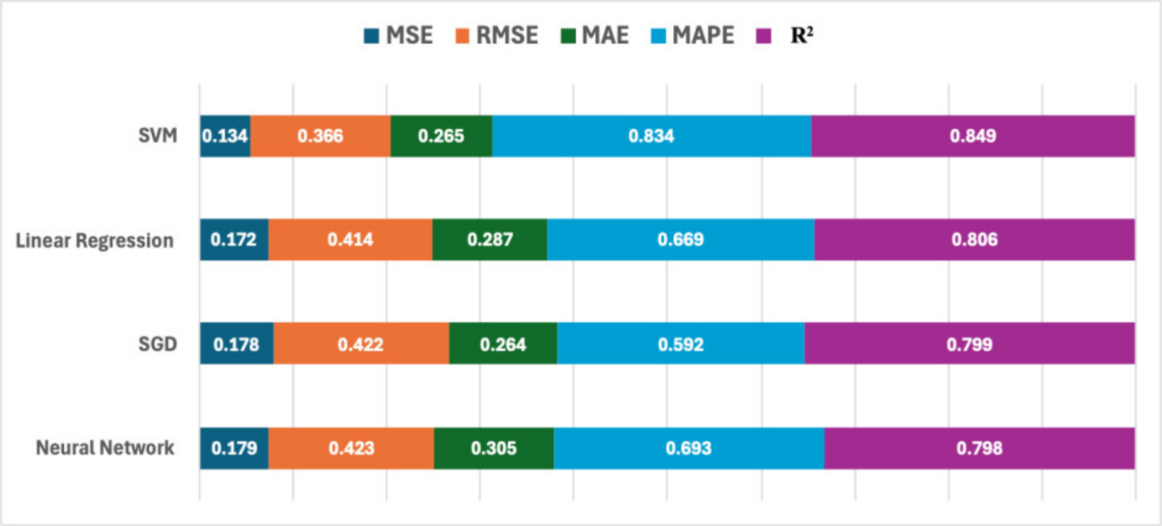

Figure 5. The performance metrics, MSE, RMSE, MAE, MAPE, and R2, used to compare model results were computed via stratified 5-fold cross-validation for predicting the maximum total production of *Cornu aspersum*.

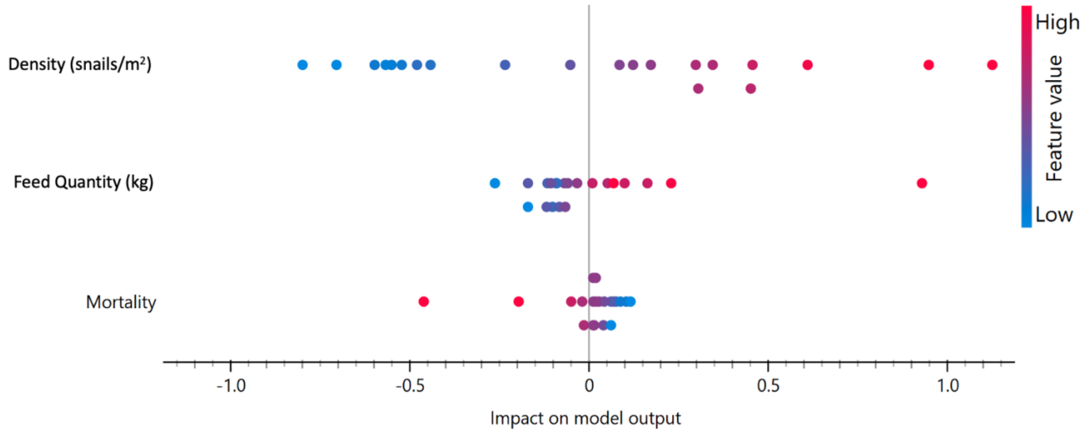

Figure 6. Explanation of the SVM algorithm on which features contribute the most and their relative contribution toward the production of *Cornu aspersum maximum* in Hellenic snail farms.

4. Discussion

The predictive model developed in this study identified snail density, mortality rate, and feed quantity as the most significant variables affecting production output in *Cornu aspersum maximum* farming, demonstrating high accuracy.

4.1. Snail Density (Snails/m^2)

Snail density is widely regarded as a key factor influencing reproduction and productivity in snail farming [85]. Many studies have demonstrated that snail density significantly affects growth, reproductive performance, total biomass, and farm productivity [86,87]. High densities are often associated with higher mortality rates [88] and reduced growth [89,90]. In contrast while lower densities tend to result in greater individual weights, they can also lead to increased adult mortality [91]. High densities have also been shown to negatively impact reproduction, resulting in limited total production [92–94]. Similarly, studies by Lazaridou-Dimitriadou et al. [95] and Mayoral et al. [96] identified a strong influence of low densities on both mortality and growth in *Helix aspersa* (= *Cornu aspersum*). Low-density may result in suboptimal biomass accumulation and thus lower overall production levels.

Additionally, Apostolou et al. [85] reported that pest infestation in net-covered greenhouses was more prevalent under high-density, particularly during intensive mating periods [22]. As a result, several researchers [90,96,97] have recommended reducing stocking density after the initial month of breeding to maintain a healthier rearing environment. In contrast, maintaining an optimal snail density throughout the breeding period allows farmers to achieve maximum individual growth and reproductive rates without reducing total biomass. Dupont-Nivet et al. [91] observed maximum growth at moderate densities, while González et al. [98] found that average densities combined with a balanced feed supply did not significantly affect final body weight.

These findings underscore the complex relationship between density and key performance indicators in snail farming. Optimal density must be carefully adjusted based on regional climate conditions, farming system type, and production goals. Proper management of density is thus essential not only for maximizing productivity but also for minimizing health risks within the production system.

4.2. Feed Quantity (kg)

Research in snail farming has demonstrated that both quantity and composition of feed significantly impact growth rate, mortality, feed conversion efficiency (FCR), and production cost. Feeding practices vary across farms: farmers rely on conventional feeds such as leaves, fruits, and plants [99], while others prefer commercially compounded diets [100]. For optimal outcomes, feed should be offered ad libitum every other day. A common and effective feeding strategy includes the use of a compound diet for first age broiler chicks, which is high in protein and typically supplemented with at least 25% calcium carbonate [101]. Protein-rich diets have been shown to improve growth rates and reduce overall feed costs [100]. Calcium plays a crucial role in shell formation and snail growth, while magnesium is important for enzymatic activity. Therefore, achieving a proper balance of nutrients is essential for optimizing not only growth but also shell characteristics and meat composition [102]. Recent studies confirm that calcium-enriched diets can significantly improve growth, survival rates, and FCR in *Cornu aspersum maxima* [3]. In addition, if nutrients are available in feed (lipids, calcium) might enhance offspring survival [103].

Feed cost represents one of the largest operational expenses in snail farming, making it a highly sensitive factor in overall farm profitability. Economic analyses of snail farms in Southern Greece have indicated that annual feed expenditures can reach approximately €13,445 in a standard net-covered greenhouse operation [68]. Consequently, even small improvements in FCR through enhanced feed management can yield substantial gains in productivity and economic efficiency. Both underfeeding and overfeeding can affect production performance of a snail farm: insufficient feeding leads to reduced individual growth rates, while overfeeding—especially with low-quality feed—can decrease FCR efficiency and increase waste and costs [3].

Taken together, these findings underscore the significance of strategic feed management in heliciculture. Investing in nutritionally balanced, cost-effective feeds that meet snails' specific dietary requirements can reduce mortality, improve feed efficiency, and increase total production output. Effective feed strategies not only enhance production performance but also contribute significantly to the economic sustainability and profitability of snail farms.

4.3. Mortality Rate (%)

Mortality rates in snail farming significantly impact productivity and are influenced by a range of biotic and abiotic parameters. Environmental conditions, particularly temperature and humidity [104,105], play a crucial role in mortality rates. Significant temperature fluctuations have been shown to increase juvenile snail mortality, especially during periods of environmental stress [106]. In adult snails, increased mortality often occurs during the initial adaptation to the new environment in the farming facility (up to 30 days) [85] and following oviposition, when physiological exhaustion is common [107].

High mortality is also associated with suboptimal management practices, such as high density, inadequate or poor-quality feed, and unsuitable substrate conditions [87]. Furthermore, mortality tends to be slightly higher in intensive farming systems compared to semi-intensive or extensive ones, likely due to increased stress and parasite transmission under crowded conditions [85,87,91,108,109].

Abiotic factors also affect snail immune resistance, increasing susceptibility to parasitic infections. Terrestrial gastropods are known hosts or intermediate hosts for several pathogenic nematodes (*Phasmarhabditis hermaphrodita* and *Alloionema appendiculatum*) which can proliferate rapidly under captive rearing conditions [22,110–113]. When hygiene protocols are not maintained, especially under high-density conditions, parasite transmission accelerates, significantly increasing mortality [111].

To reduce mortality and optimize productivity, snail farmers should employ management strategies, including early harvesting, as well as proper environmental conditions and housing and feed quality control [87,107]. Lowering mortality in both juvenile and adult stages significantly enhances the sustainability and economic feasibility of snail farming.

4.4. Machine Learning and Artificial Intelligence

The integration of ML technologies in livestock production is demonstrating substantial impact. It enhances productivity, optimizes resource use, improves animal welfare, and enables accurate production forecasting [26,114–116]. Numerous studies have demonstrated the application of advanced technologies, including AI and ML, across various livestock management domains, such as cattle, pig, and dairy production systems [26,47,117,118].

ML applications in animal farming have shown significant improvements in productivity by processing large datasets from sensors and monitoring systems [114,117,119]. In our study, as well as in similar work across other livestock sectors, predictive models demonstrated over 85% accuracy in estimating farm productivity, despite challenges such as data quality [120]. The use of ML techniques will help identify and prioritize key factors influencing the adoption of breeding methods to enhance the heliciculture sector.

Furthermore, digital tools enable more precise management of breeding, nutrition, and welfare, improving sustainability [26,119]. Also, farmers by analyzing the data obtained from ML techniques can optimize input use, particularly feed, which remains one of the highest operational costs. This approach not only enhances economic efficiency but also lowers the carbon footprint of the production system.

Ultimately, integrating ML and related technologies into snail farming holds significant potential to promote sustainable, environmentally friendly, and economically viable production through precise forecasting, improved planning, and optimized resource allocation.

5. Conclusions

This is the first study to employ ML techniques to model production output in *Cornu aspersum maximum* snail farms. The analysis identified snail density, feed quantity, and mortality rate as the most influential variables affecting productivity. Among the tested models, the Support Vector Machine algorithm demonstrated the highest predictive accuracy (85%), highlighting its utility for decision support in heliciculture.

These findings offer a significant step toward the digital transformation of small-scale livestock systems. Machine learning can support more precise management by enabling farmers to optimize stocking density, improve efficiency, and reduce mortality. By leveraging predictive analytics, snail farms can minimize resource waste, enhance profitability, and adopt more sustainable practices.

Importantly, by lowering avoidable losses through improved forecasting, machine learning contributes directly to reduced production costs. Economic impacts of mortality are considerable, as elevated death rates increase costs per unit of output and diminish overall farm profitability.

Moreover, the clustering analysis revealed two distinct farming strategies, underscoring the importance of tailored management approaches based on environmental and operational conditions. This research provides a foundation for future integration of real-time data and sensor technologies in snail farming.

To build on this work, future research should prioritize expanding datasets to include a broader range of geographic regions and incorporating continuous environmental monitoring. Such advancements will improve model robustness and support the broader adoption of artificial intelligence tools in heliciculture and other alternative livestock sectors.

Author Contributions

Conceptualization, K.A. and M.H.; methodology, K.A.; software, D.K.; validation, K.A., M.H. and D.K.; formal analysis, K.A.; investigation, K.A.; resources, M.H.; data curation, K.A.; writing—original draft preparation, K.A.; writing—review and editing, M.H. and D.K.; visualization, D.K.; supervision, M.H.; project administration, K.A.; funding acquisition, M.H. All authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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