JTRET "Voice of Innovative Minds"
International Journal Trendy Research in Engineering and Technology
Volume 8 Proceedings of NCCDS-24
ISSN NO 2582-0958

SILKWORM YIELD PREDICTION: EXPLORING LEAF TYPES AND SPECIES

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ABSTRACT

This study investigates the application of two distinct machine learning models, Random Forest and Linear Regression, to predict the yield of silkworms based on the type of leaves and species. Silkworms are crucial in the silk production industry, and understanding the factors influencing their yield is essential for optimizing sericulture practices .The dataset utilized in this research comprises information on silkworm yield, leaf types, and species characteristics. The Random Forest model, known for its ensemble learning capabilities, demonstrates its effectiveness in capturing complex relationships between predictor variables and silkworm yield .Comparative analyses between the two models reveal nuanced insights into the predictive capabilities of each approach. The results of this study contribute to the optimization of sericulture practices by offering a comprehensive predictive framework.

Keywords : *Machine Learning models, Mulberry Leaf, Random forest Regression, Linear Regression.*

I. Introduction

About 97% of India's mulberry silk is produced due to its climate suitable for annual mulberry tree cultivation. Mulberry, silkworm and cocoon are used as the main products in the sericulture industry. Mulberry trees need a safe appearance to grow and develop. Proper nutrition of mulberry leaves is important for raising silkworms and producing biomass. Many farmers don't pay attention to the condition of the soil and the abiotic bacteria that make the nutrients in the leaves, and so when the silkworms eat them, they don't produce great pieces of silk. Sericulture involves the careful breeding of silkworms to produce silk.Silkworm rearing, an integral aspect of sericulture, involves the meticulous cultivation of silkworms for the production of silk. This ancient practice has evolved over centuries, intertwining with cultural, economic, and technological advancements. Central to successful silkworm rearing are considerations regarding the species of silkworm and the types of leaves they consume.Species diversity in silkworm rearing plays a pivotal role in determining the characteristics of the silk produced. Among the various species, Bombyx mori stands out as the most widely cultivated and domesticated silkworm species. Renowned for its exceptional silk production and adaptability to diverse environmental conditions, Bombyx mori serves as the primary species in sericulture operations worldwide. However, regional variations and specific silk quality requirements have led to the cultivation of other species, such as Antheraea assamensis and Antheraea mylitta, in certain geographic areas. The choice of food for silkworms is equally crucial, as it directly influences their growth, development, and silk production. Silkworms are voracious feeders, primarily consuming leaves from mulberry trees (Morus spp.). Mulberry leaves are nutritionally rich and provide the essential nutrients required for silkworm larvae to undergo metamorphosis and spin their cocoons. The quality of the leaves, including factors such as freshness and nutritional content, significantly impacts the yield and quality of silk produced.Beyond mulberry leaves, certain silkworm species exhibit adaptability to a range of host plants. Polyphagous species, for instance, can thrive on a variety of plants, expanding the scope of sericulture to regions where mulberry cultivation might be challenging. Understanding the interplay between silkworm species and their dietary preferences is fundamental to optimizing rearing practices and ensuring sustainable silk production.As we delve into the intricate dynamics of silkworm rearing, this exploration encompasses the diverse spectrum of silkworm species and their dietary requirements. By unraveling the intricacies of this symbiotic relationship between silkworms and their environment, we gain insights that contribute to the enhancement of sericulture practices and the cultivation of this coveted natural fiber.

A. *Adaptive models*

Machine learning's strength: Advanced machine learning algorithms can handle these diverse datasets by identifying latent patterns and relationships between different leaf types, environmental factors, and yield outcomes.

• Flexibility and scalability: As more data on alternative leaves accumulates, these models can adapt and refine their predictions, offering farmers greater flexibility and choice in their feeding practices. Overall, incorporating different leaf types into silkworm yield prediction adds complexity but also unlocks exciting possibilities. By embracing machine learning and continuously collecting data, we can develop robust models that guide farmers towards optimal leaf choices for sustainable and high-yielding sericulture.

II. Literature Survey

Sakthivir et al. [1] suggested organic farming in the mulberry garden, saying that organic fertilizers play an important role in the health of the soil by improving the physical, chemical and biological properties of the soil. The two methods are physical (water column) and biological. Biological methods play an important and unnecessary role in controlling important pests in mulberry gardens, because chemical products such as weak fertilizers, pesticides, pesticides and fungicides are used every two months in the mulberry garden, which not only harms the ecosystem, but also harms the ecosystem. Negative effects on mulberry gardens. Soil health and hazards to humans and beneficial organisms, including silkworms.

Sharma et al. [2] applies machine learning for precision agriculture, also known as smart agriculture, which was developed as a new tool to solve the current problems of agricultural development to make the farm sustainable. The driving force behind this technology is machine learning (ML). Combining machine learning with the Internet of Things (IoT), agricultural machinery is an important part of the future of agriculture. In this article, the authors present a systematic approach to machine learning in agriculture. Machine learning is used in conjunction with computer vision analysis to identify different product types to monitor product quality and predict yield.

Chorshanbi Bekkamov et al. [3] The nutrition and nutritional quality of silkworms in the early stages of development, as well as their exposure to poisons and diseases, have a great impact on the quality of the organisms in the larvae and the body of the organisms in the cultivated plants. Improve the quality of the cocoon: Eating a healthy diet and reducing exposure to toxins and bacteria in the early stages can make the cells along with the cancer cells healthier.This translates to cocoons with thicker, stronger silk filaments, increasing their commercial value. Increased silk yield: Healthy silkworms tend to grow faster and produce larger cocoons, resulting in a higher overall yield of raw silk per rearing cycle.

Shilpa Saikia and Monimala Saikia [4] discussed on sericulture process of nurturing silkworm to produce silk. Many biotic and abiotic factors are responsible for growth and development of silkworm. Precision farming: Sensors and automated systems can monitor temperature, humidity, light, and other environmental factors in silkworm rearing houses, allowing for precise control and optimization of conditions for better growth and cocoon quality. Real-time data and insights: IoT sensors can collect data on various parameters like silkworm activity, feeding behavior, and cocoon formation, providing real-time insights into the rearing process and enabling early detection of potential problems.

Manoj S M [5] imposed goals to improve both farmland and cocoon production for better results in the future. Improved planning and resource allocation: Predicting silkworm yield can help farmers optimize resource allocation, such as mulberry leaves ,labour , and rearing space, based on expected production. Data-driven decision making: Machine learning models can analyze historical data on weather, rearing practices, and silkworm performance to identify factors influencing yield, enabling data-driven decisions for improved production.

Palguni Bhattacharyya et al. [6] proposed on Silkworm rely on mulberry leaves during their larval stage and are primarily fed white mulberry. Increased efficiency and control: Artificial diets can be formulated to deliver precise nutritional requirements, potentially leading to faster growth, better cocoon quality, and improved disease resistance. Improved year-round production: Mulberry availability is seasonal, but artificial diets can be readily made at any time, enabling year-round silkworm rearing and a more stable income for farmers.

Anca Gheorghe et al. [7] proposed about Silkworms, crucial in sericulture, typically feed on nutrient rich mulberry leaves, known for compounds like morin and antioxidants. The importance of nutrition in silkworm rearing and the effectiveness of artificial diets for their productivity and health .Highlights the importance of nutrition: Mulberry leaves rich in nutrients like morin and antioxidants are vital for silkworm growth and cocoon quality. Recognizing this connection emphasizes the need for proper nutrition in sericulture .Introduces artificial diets as an alternative: Mentioning artificial diets opens up the possibility of alternative food sources for silkworms, potentially addressing challenges like mulberry cultivation or seasonal variations.

III. PROBLEM DEFINITION AND METHODOLGY

1) ***Problem Definition*:** Developing a precise Silkworm Yield Prediction model is essential for optimizing silk production. This project focuses on exploring the impact of leaf types and species on silkworm yield. By utilizing machine learning techniques and considering variables like age, batches, temperature, and past yield data, the goal is to create a predictive model that enables sericulturists to anticipate and enhance silkworm productivity. The project aims to address the complexities of sericulture, providing valuable insights for informed decision- making in the cultivation process.

2) ***Methodology:*** A level-3 heading must be indented, in Italic and numbered with an Arabic numeral followed by a right parenthesis. The level-3 heading must end with a colon. The body of the level-3 section immediately follows the level-3 heading in the same paragraph. For example, this paragraph begins with a level-3 heading. This study investigates the application of two distinct machine learning models, Random Forest and Linear Regression, to predict the yield of silkworms based on the type of leaves and species. Silkworms are crucial in the silk production industry, and understanding the factors influencing their yield is essential for optimizing sericulture practices. The dataset utilized in this research comprises information on silkworm yield, leaf types, and species characteristics. The Random Forest model, known for its ensemble learning capabilities, demonstrates its effectiveness in capturing complex relationships between predictor variables and silkworm yield. Comparative analyses between the two models reveal nuanced insights into the predictive capabilities of each approach. The results of this study contribute to the optimization of sericulture practices by offering a comprehensive predictive framework.

a) Data Preprocessing: The resulting data is preprocessed by removing all null and irrelevant values. Relationships between features were analyzed. There are many values in the data set, and they are all normalized to a value between 0 and 1. The purpose of normalization is to bring all values into range.

b) Training the model: At this stage, the model is trained according to the training process. Various horizontal, ridge regression and random forest regression models were used to train the data set and the accuracy of these models was compared.

i) First, use multiple linear regression. It is a statistical method that uses more than one explanatory variable to predict the final outcome of a set of variables. Multiple linear regression (MLR) is used to find the relationship between independent and hypothesized variables.

ii) Second, due to its simplicity, interpretability, and versatility, linear regression is used in statistics and machine learning for many reasons. The relationship between the success and independence variables is shown as a linear equation. Once a model is on historical data, it can be used to make predictions about changes in new or unseen data.

iii) Random Forest regression is an also applied. It is supervised machine learning algorithm that is constructed from decision tree. It utilizes ensemble learning that combines many classifiers to provide solutions to complex problems.

c) Testing the model: After training, the accuracy and precision of multiple regression models will be tested. Testing methods will be used to evaluate the model and relevant observations will be recorded.

d) Output - Yield prediction: The model used will predict mulberry leaf yield depending on the silkworm species and mulberry leaves taken as input.

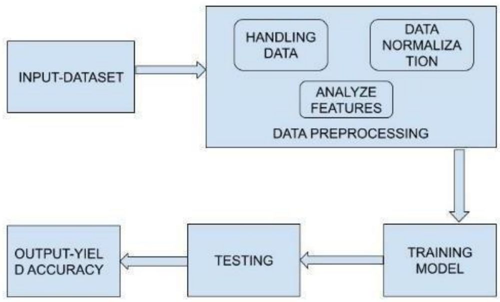

Fig1:Silkworm yield prediction model

IV. EXPERIMENTAL RESULTS

1) Experimental Setup

The experimental setup employed in this study includes a system configuration featuring Windows 10 as the operating system, 8GB of RAM, and a disk space of 512GB. The implementation of the study was conducted using the Python programming language. Furthermore, the data utilized in this experiment was collected from online colleges, providing a diverse and relevant dataset for analysis.

2) Data Preprocessing

Parameters: Variables: Batch, age (days), number of cocoons, cocoon weight (grams), temperature (°C), humidity (%), yield data Correlation test: Pearson correlation coefficient (PCC), for example from -1 (Strong) negative correlation) to +1 (strong positive correlation) color harmony: there may be a shift from blue (negative correlation) to red (positive correlation); white or neutral color indicates no relationship.. Weaker correlations with Number of Cocoons: The number of cocoons doesn't show strong correlations with other variables, indicating potential independent factors influencing it. Contextualize findings: Relate these findings to domain knowledge and specific research questions to draw meaningful conclusions. Cocoons have strong to moderate positive correlations with Temperature, Humidity, and Yield Data. The number of cocoons doesn't show strong correlations with other variables, indicating potential independent factors influencing it. While the heatmap shows pairwise correlations, it's important to consider potential interactions between variables that might not be captured here.

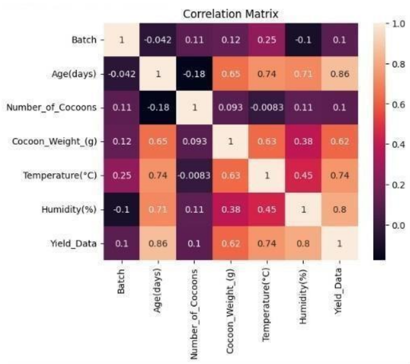

Fig 2 Heatmap demonstrating the relationship between the various attributes

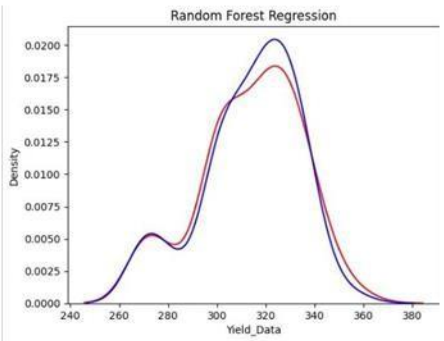

Fig 3 Comparison of Accuracies of Machine Learning models

The above discussion focused on a scatter plot with a superimposed density plot showing the relationship between yield data and an unknown feature (Batch, Age, Number of Cocoons, Cocoon Weight, Temperature, or Humidity).Key Takeaways from the figure is, The yield data distribution is right-skewed, with a peak around 0.3.Potential correlations exist between yield data and the feature, but the specific feature needs to be identified for accurate interpretation. The diagram helps identify trends, outliers, and potential correlations.

CONCLUSION

In summary, our study on silkworm yield prediction using machine learning and considering different leaf types and species has revealed important insights for sericulture. We found that the type of leaves significantly influences silkworm yield, and understanding these variations is crucial for optimizing cultivation. Additionally, each silkworm species responds differently to environmental factors, highlighting the need for tailored practices. The machine learning models we applied, such as Decision Tree Regression and Gradient Boosting Regression, demonstrated strong predictive abilities, providing a glimpse into the future of sericulture planning. These findings empower farmers with tools for precision agriculture, helping them optimize resources and manage risks. The study contributes to industry innovation, fostering a more resilient and sustainable future for silk production. Future research may explore additional variables and advanced techniques for further improvements. Overall, our project offers valuable insights for enhancing sericulture practices and productivity.

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