Prediction of internal moisture in post-harvest cocoa (*Theobroma cacao*) using a machine learning system, applicable to farms that use solar drying.

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Abstract— This article explores the potential for predicting moisture content in cocoa post-harvest using a machine learning system that incorporates experimental data and accounts for varying temperature conditions. Key post-harvest processes, such as fermentation and drying, significantly influence the quality of the final product, but humid and rainy climates in cocoa-growing regions complicate these processes, necessitating improved technologies. The methodology involves developing a prediction engine utilizing a Multilayer Perceptron (MLP) with MLPClassifier and MLPRegressor classes, employing experimental field data and two data-generating models: an automatic moving boundary model for isothermal food dehydration and the Brusselator model for autocatalytic reactions. A total of approximately 2,500 experimental data points were collected from six tests conducted between June and December 2023. The neural network was designed to accept a convergence interval of experimental results for 70% of the training data, with the remaining 30% used for verification. The prediction engine achieved an accuracy range of 78% to 82%. The implementation of Adrover's isothermal dehydration model proved beneficial, preventing non-convergence and showcasing effective convergence-accelerating algorithms. The system can make predictions for up to 420 hours based on experimental results. Ultimately, the study presents a predictor for post-harvest cocoa conditions using an artificial neural network that effectively accounts for temperature variability, making it suitable for artisanal cocoa processing. However, it emphasizes the need for additional data to improve mean squared error (MSE) and R^2 values, and suggests future research should include genetic diversity of cocoa lots to enhance prediction accuracy.

Keywords— *Dehydration, Post-harvest, Theobroma cacao, Artificial neural network, Humidity predictor*

I. Introduction

The cocoa tree, scientifically known as *Theobroma cacao L.*, belongs to the Malvaceae family, with "*Theobroma*" meaning "food of the gods" in Greek and "*cacao*" derived from the Nahuatl word "cacáhua" Cacao is the primary raw material for chocolate production [1]. Post-harvest handling of cocoa involves critical processes such as removing seeds from ripe fruit, fermentation, and drying, which are essential for achieving optimal quality characteristics, including organoleptic properties and safety [2, 3]. The aim is to allow producers to competitively sell their cocoa in regional and international markets [4].

Post-harvest operations start with seed removal, leading to fermentation in the pulp surrounding the seeds, which significantly affects the seeds' color and flavor, ultimately influencing the final product's quality [2]. Following fermentation, drying is crucial for reducing moisture content and acetic acid levels to prevent microbial deterioration [3]. While drying can be carried out through natural or controlled artificial methods, many small and medium producers lack access to the necessary technology for controlled drying [1].

The humid and rainy climate typical of cocoa-growing regions complicates drying and storage, increasing the risk of mold and undesirable microorganisms [5]. As a result, many agroecological farms depend on manual drying, which often leads to inconsistent quality.

Cocoa farming is economically significant for smallholders in rural areas of Africa, Latin America, and Asia, highlighting the need for improved processing technologies [1]. This has led to initial attempts to predict the final conditions of post-harvest cocoa using phenomenological models such as those proposed by [6, 7, 8, 9], among others. These models are useful under controlled temperature conditions but not for processes where such parameters cannot be controlled. To predict final conditions in oscillatory or chaotic processes, such as artisanal cocoa post-harvest, predictive models based on Machine Learning have been developed in recent years [10].

Phenomenological models, including microscopic and macroscopic types, establish mathematical relationships to describe real processes [6, 8]. For example, the moving-boundary model for isothermal dehydration estimates water diffusion effects during cocoa seed drying [8]. This model addresses the heterogeneous water distribution within cocoa beans and divides the drying process into rapid and slow phases [9]. Although cocoa post-harvest processing is not conducted isothermally, this model can be useful for approximating the first iteration and accelerating the

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convergence of the prediction algorithm, as well as for adjusting the weights of the loss function.

Machine learning, as Artificial Neural Networks (ANN), enhances cocoa post-harvest processes by integrating experimental data [11]. ANN are effective for various applications in the food industry, including quality prediction [12]. The utilization of adaptive learning and self-organization enables Artificial Neural Networks (ANN) to operate effectively in chaotic processes, such as those encountered in post-harvest cocoa management [13].

The review by Tamayo, Ferrancol, and Romeroso in 2024 [11], analyzes 36 selected publications focusing on machine learning (ML) applications in cocoa post-harvest management. The study highlights three primary areas: classification of cacao pods, quality assessment, and fermentation monitoring. Accurate classification is essential for maintaining product quality, as manual sorting can lead to contamination and misidentification of varieties. Various models, including Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs), have been employed to enhance classification accuracy [14]. For instance, a CNN-based model was developed to classify healthy and diseased cacao pods, while an ANN demonstrated effectiveness in distinguishing between healthy and unhealthy beans using color features [15].

In the context of quality assessment, traditional methods relying on manual inspection are being replaced by automated systems that utilize ML algorithms. Notably, an ANN was used to classify beans into good, fair, and bad categories, achieving high accuracy [16]. One of Other studies employed techniques like support vector machines (SVM) and backpropagation neural networks to enhance the efficiency of quality evaluation, indicating a shift towards AI-driven methodologies in this area [11].

The multilayer perceptron (MLP) is a type of algorithm for Back-propagation Artificial Neural Networks that acts as a learning function by training on a dataset [17]. The implementation of Multi-layer Perceptrons (MLP) in the Scikit-learn 1.4.1 library (Python 3) enables supervised learning and improves convergence rates through techniques like Stochastic Gradient Descent (SGD) and the ADAM optimization algorithm [18]. The Adrover model (2020) provides ideal humidity data to facilitate the training of predictive models, while the Brusselator model helps manage random variations in moisture dynamics according to [13]. MLP uses the MLPRegressor class, which employs two metrics to evaluate the model's performance during training: the coefficient of determination R^2 and the mean squared error (MSE) [19]. The "mean_squared_error" function calculates the MSE, which is a risk metric representing the expected value of the squared error or loss. On the other hand, the "r2_score" function computes the coefficient of determination, commonly denoted as R^2, which indicates the proportion of the variance in the output values 'y' that is explained by the independent variables in the model. This allows for accurate predictions on unknown samples through the proportion of variance. The maximum possible value of R^2 is 1.0, indicating a perfect fit of the model. However, the coefficient of determination can also take negative values, which means that the model performs worse than random guessing [17].

MLP also uses the MLPClassifier class, which learns the backpropagation algorithm, allowing adjustments to the system's loss function. The general objective of the research is to determine whether it is possible to predict the moisture value in cocoa post-harvest using a machine learning system that uses experimental data to develop a methodology considering variable temperature conditions.

II. METODOLOGY

The methodological procedure involved the construction and implementation of engine for predicting moisture during post-harvest processes (moisture predictor). This system employs Multilayer Percerptron (MLP), with its two classes : MLPClassifier and MLPRegressor [17], using experimental field data and supported by two data-generating models to enhance prediction convergence. The first model is the automatic moving boundary model for isothermal food dehydration explained in [9], and the second is the Brusselator model described in [13], which describes the kinetics of oscillatory autocatalytic reactions, such as cocoa fermentation [13, 20]. The algebraic development carried out to standardize the parameters of the Adrover model and the Brusselator model with experimental data, making it processable by the learning engine, was addressed in Chapter 2 in [21].

To enhance understanding of the methodological structure employed, Figure 1 is presented, which outlines the stages that comprise the methodology for constructing the moisture predictor. Due to formatting and space constraints, the theoretical and algebraic development of the phenomenological models used, as well as a detailed description of the functioning of the proposed machine learning tools, will not be covered in this document. Instead, it is recommended to consult in [21] for further clarification.

a.

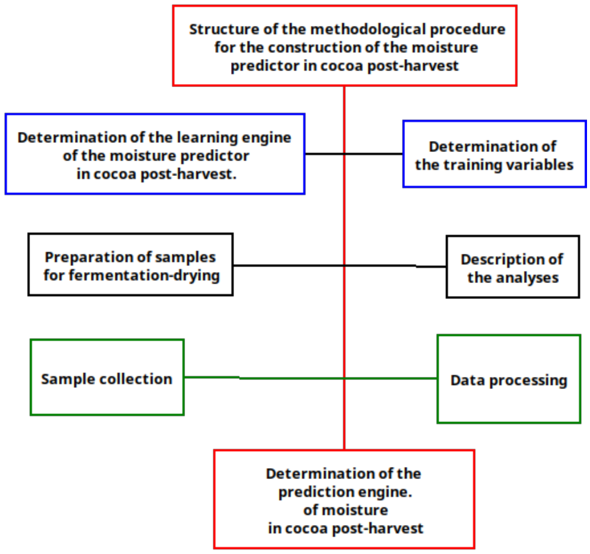

Fig. 1. Methodological sequence used for the construction of the moisture predictor.

Training variable Determination: after configuring the learning engine of the moisture predictor, the training variables were established. These physical and chemical parameters were experimentally determined through various cocoa porharvesting tests. The data help define convergence interval limits [19]. The training variables were selected based on logistical availability and instruments, with six non-simultaneous tests conducted using cocoa from the CATIE collection. Key variables considered included:

Internal Cotyledon Moisture: drying concludes when seed moisture reaches 6-7% [22].

pH: the lowest pH is expected on day 6 of post-harvest due to the formation of acetic and lactic acid [23].

Temperature in Pulp/Shell: expected to peak during fermentation [22] .

Mass: initial and final mass measurements indicate water loss from the seed [24].

Dimensions: measuring initial and final dimensions allows for calculating seed contraction volume [25].

External Moisture (Pulp-Shell): influences dehydration rate and diffusion flow direction [26].

Sample Preparation for Fermentation and Drying: Cocoa pods from the CATIE collection were manually opened in the fields. Fermentation boxes, measuring 60 cm on each side and 10 cm thick, were prepared, with a layer of banana leaves added as a microbial inoculum. Each box contained 70 kg of cocoa.

Fermentation and Drying Conditions: fermentation began within 24 hours of pod opening, lasting 6 to 7 days. After fermentation, pre-drying commenced on day 7 (or day 8 in one case) using Rohan boxes. The operation was characterized by temperature variations throughout the process. Pre-drying lasted 24 hours, followed by sun drying in Rohan boxes for tests 1 to 4, while tests 5 and 6 utilized a greenhouse setup.

Analysis Description: The variables described were aimed at providing training data for the algorithm. The following analyses were conducted to generate theoretical training values necessary for machine learning algorithm input. Data obtained under varying conditions of temperature, humidity, height, and seed dimensions served as reactive samples.

Internal Cotyledon Moisture and Calibration Curve: moisture at any time was determined using the ISO 2291-1972E method, involving a 25 g cocoa sample heated at 130 °C for 16 hours, with moisture calculated by weight difference, between the sample before thermal treatment and after it. Daily moisture measurements helped establish a calibration curve considering water diffusivity effects on moisture rate [9]. As a result, the moisture content of each sample over time is obtained, expressed as g of water/g dry base. However, for presentation purposes, it is advisable to express the result as a percentage of relative humidity, as shown in Figure 2.

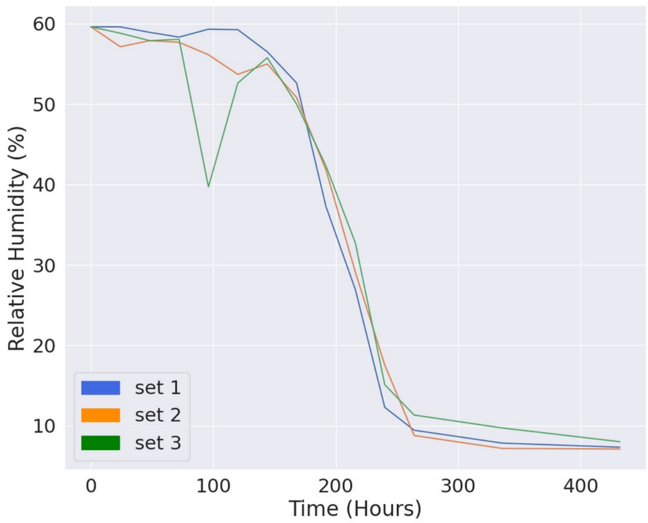

Fig. 2. Experimental calibration curve of moisture content expressed as percentage relative humidity over time.

Seed Dimension Measurement: measuring seed dimensions at the start and end of the process allowed for determining the contraction factor affecting the drying operation. Average dimensions were measured using calipers across 15 seeds daily during the six fermentation-drying tests. Figure 3 shows the selection of the longitudinal axes of a cocoa seed according to [23].

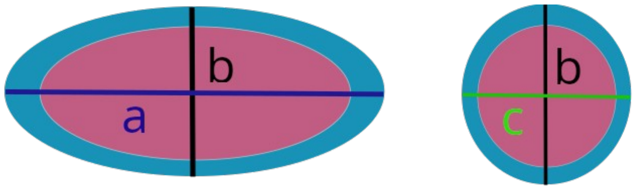

Fig. 3. Determination of the dimensions of the cocoa bean.

pH Measurement: a 25 g sample of cocoa was taken daily to measure pH, using a pH meter after dilution with water. Although pH is not the main output of the predictor for the purposes of this research, it is important to measure its variation over time (Figure 4), as this information serves as a weighting factor for the loss function in the prediction engine.

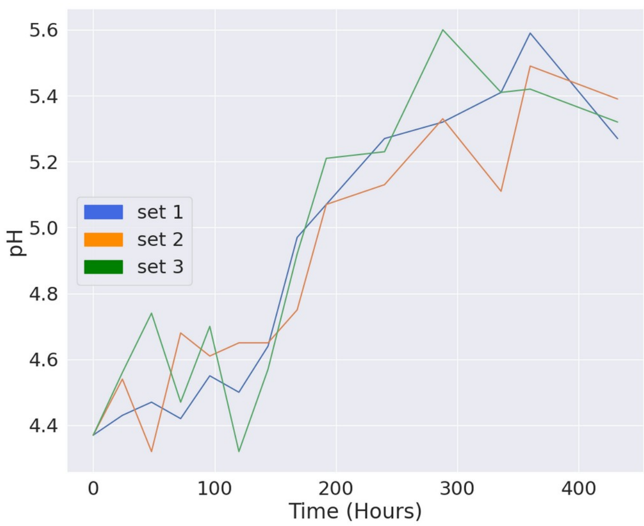

Fig. 4. Example of the experimental determination of pH over time for test number 5.

External Moisture Measurement: Flash Link MDL. 40550 Data Logger was programmed to record humidity every 30 minutes during fermentation and drying.

External Temperature Measurement: the same data logger recorded temperature every 30 minutes, with additional measurements taken using an Omega thermocouple for trials 4 and 5.

Flash Link MDL. 40550 Data Logger records data on both temperature and relative humidity in the pulp or shell of the cocoa bean, as shown in Figure 5. This allows us to see that the influence of operating conditions (temperature and ambient humidity) affects the variation in temperature and humidity

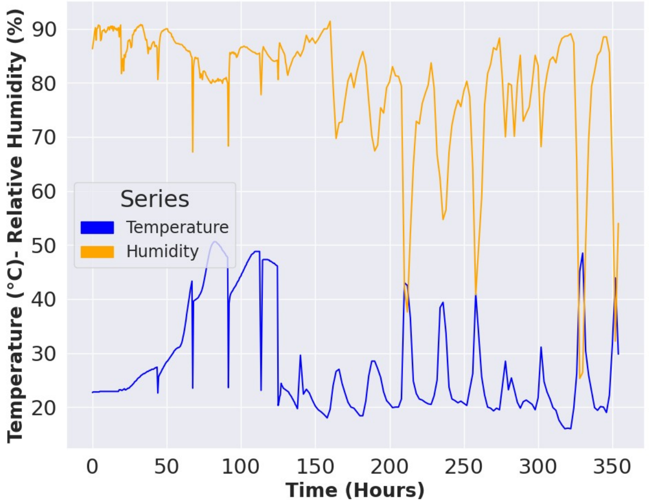

Fig. 5. Variation of temperature (°C) and relative humidity in the pulp-shell in cocoa post-harvest in test number 5.

Data Collection: six fermentation-drying tests were conducted between June 26 and December 6, 2023, with some tests including additives like zinc and amino acids. All tests were performed at the Santa Lucía experimental farm of the School of Agricultural Sciences in Barva de Heredia, providing conditions that reflect the challenges faced by small producers in regions with high humidity, such as Upala and Northern Costa Rica.

Data Processing and Learning Engine Construction: to program and train the learning engine for the post-harvest cocoa moisture predictor, experimental data was collected. The programming was devoloped in Python 3 using the Jupyter Lab platform for creating experimental graphs and implementing the Adrover (2020) and Brusselator models. Libraries such as NumPy, Seaborn, Matplotlib, SymPy, and SciPy were utilized. The neural network was also coded in Python 3 but within the PyCharm platform, specifically using the Scikit-learn 1.4.1 library [17].

Configuration of the Post-Harvest Cocoa Moisture Prediction Engine: The user interface of the post-harvest moisture prediction engine consists of an input form on the web platform, where users provide data, and an output form displaying the results. To establish the information displayed on the interface, fields must be defined for user input to yield one or more results, referred to as inputs [19]. The outputs are the results presented by the predictor after processing the input data [27].

The implemented neural network is based on a basic unit known as a multilayer perceptron. Figure 6 illustrates that the input layer represents the data required for the neuron to return a result or output layer. Both the input parameters (initial ambient moisture, ambient temperature, time, initial dimensions, and initial internal moisture) and the output parameter (final internal moisture) were determined experimentally as previously described.

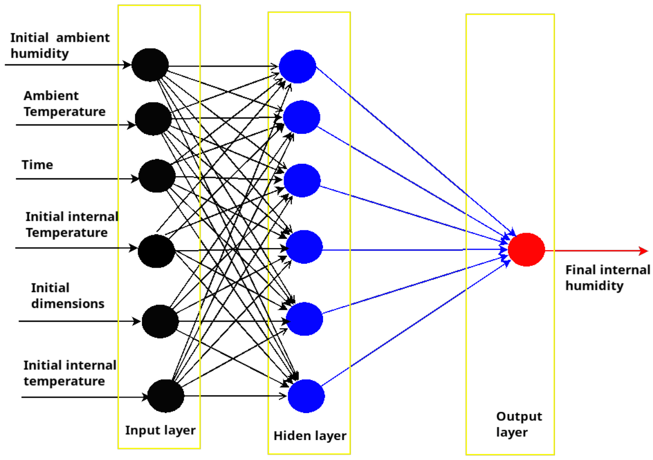

Fig. 6. Example of the structure of a multilayer perceptron, basic unit of the neural network (internal humidity predictor).

Input and Output Variable Selection: The input layer for the training of the cocoa post-harvest moisture predictor consists of several key variables. Time is measured in hours to align with the Adrover and Brusselator equations, as using seconds could result in infinite values [28]. Average dimensions of the cocoa beans are recorded across multiple trials to estimate final volume, with the model starting with a broad probability interval that narrows as learning progresses [19]. The initial internal moisture of the cocoa typically ranges from 58% to 62% [14]. Ambient temperature also plays a crucial role, affecting mass transfer coefficients and thus the speed of dehydration [26]. Additionally, the average climatic interval serves as a learning parameter related to the geographical area of processing. The output layer includes several parameters that respond to the inputs and guide the learning process. The primary output is internal moisture, which should be between 6% and 7% at the end of the post-harvest process [22, 29]. pH is another important output, indicating process quality; unusual values may indicate issues with fermentation [30]. Typically, a low pH is expected on day 6, with an increase by day 12 [23]. Finally, the final volume is estimated based on initial dimensions and the amount of water and volatile solids released during processing [31].

III. RESULTS

Six tests were taken on june 2023 to december 2023, for performing a data basis of posibles entries and its results. A discontinuous dataset of approximately 2,500 experimental data points was obtained, as various issues inherent to the type of environment being emulated (artisanal post-harvest conditions, sun drying) arose during the experimental phase. These issues included high rainfall, very high ambient humidity, and water infiltration in the post-harvest area. This led to the loss of some data, which may affect the accuracy of the results.

TABLE I. TESTS CONDUCTED AT THE EXPERIMENTAL FARM OF THE SCHOOL OF AGRICULTURAL SCIENCES IN SANTA LUCÍA DE BARVA

Test number	Repeats	Performed analyses
1	1	Internal moisture
2	1	Internal moisture, internal pH, longitudinal dimensions of the seeds, external relative humidity, external temperature
3	2	Internal moisture, internal pH,

		longitudinal dimensions of the seeds, external relative humidity, external temperature
4	3	Internal moisture, internal pH, longitudinal dimensions of the seeds
5	3	Internal moisture, internal pH, longitudinal dimensions of the seeds, external relative humidity, external temperature
6	2	Internal moisture, internal pH, longitudinal dimensions of the seeds, external relative humidity, external temperature

Construction of the Neural Network: the construction of the neural network involved consulting various models and algorithms, which often use different notations. For clarity, this study adopts the notation used in the isothermal dehydration model by Adrover (2020).

Processing of Experimental Data: results from all analyses were classified and stored in a database, allowing the post-harvest cocoa condition predictor to query this database with each iteration. Additionally, when users input new experimental data, the predictor learns a reliable new result, which is then added to the existing database for future queries.

After the experimental data is collected, a matrix is created for each variable, defined as the convergence interval of the experimental results. The neural network is programmed to use this interval as the acceptance limit for 70% of the training data [19]. Therefore, whenever a prediction falls outside the convergence interval, it is necessary to provide feedback with an experimental value so that the system can learn the convergence path according to the conditions. If needed, the convergence interval may be adjusted for the given conditions [14, 15]. The set of learning algorithms is referred to as the learning engine [10, 13].

Training Functions: Seventy percent of the dataset was used for training, while the remaining 30% was used for verification tests. In other words, the learning engine was first trained, and then it was checked that the predicted results fell within the convergence interval. This proportion is recommended by both the creator of the Scikit-learn library 1.4.1 in [17] and by Olofintuyi in [19]. These researchers validated the arrangement of 70% / 30% through a series of experiments analyzing the efficiency of the predictive models studied. Some of the efficiency indicators used include mean absolute error, mean squared error, among others [19].

Convergence Intervals Definition: the convergence intervals of the neural network represent the expected output based on experimental results [19]. The neural network learns from real experimental data, adjusting predictions to minimize the loss function, ideally achieving $R^2 \rightarrow 1$ and mean squared error (MSE) $\rightarrow 0$ [17]. If predictions fall outside the convergence interval, the system must be retrained with new experimental values [14, 15].

The data generated through the training variables were processed into a matrix. The convergence intervals for the internal relative humidity of cocoa beans (algebraically related to moisture content) and for pH are graphically presented in Figure 7. It is worth mentioning that the graphs corresponding to the remaining training variables were calculated and incorporated into the system, although they are not presented in this document.

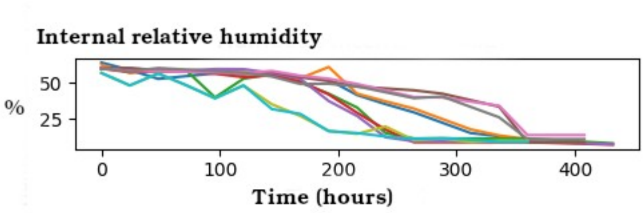

Fig. 7. Experimental convergence interval for internal relative humidity.

Data Integration and Training: The MSE estimates the total deviation between predicted and actual values, while the coefficient of determination R^2 indicates data correlation [33]. After multiple iterations, the MSE was 153, suggesting the need for additional experimental data to improve accuracy, with an R^2 of 0.82 indicating reasonable predictive performance [31].

TABLE II. TESTS CONDUCTED AT THE EXPERIMENTAL FARM OF THE SCHOOL OF AGRICULTURAL SCIENCES IN SANTA LUCÍA DE BARVA

Metrics	**Trainnig 1**	**Trainnig 2**
Mean squared error (MSE)	153	112
Coefficient of determination: R^2	0.82	0.78

Figure 8 displays the graphical result of the integration of information and training of the learning engine for the variable internal relative humidity**.** This graph represents the results obtained in training 1.

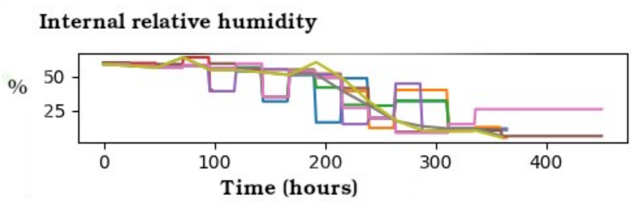

Fig. 8. Experimental convergence interval for internal relative humidity.

From the results obtained, it can be inferred that the accuracy interval for the proposed prediction engine ranges from 78% to 82% [17]. According to the classification proposed in [10], this predictor is classified as: Implementation of MLP adjusted with backpropagation.

The proposed arrangement of MLP models in this research resembles 1 study from the 36 publications classified by [10], in which an MLP with backpropagation is implemented; however, this research [32] only use the Classifier function (obtained a 92,7 % of accuracy), while the proposed predictor also implements the Regressor function and uses Adrover's dehydration model to accelerate the convergence of the loss function and reduce the iterations of the predictor. Due to the model proposed by [32], predicts attributes such as slate, mold, free fatty acid, and foreign matter, among others, through image recognition, is not allow for comparison between both. However, this research provides information for decision-making for future investigations in machine learning applied to cocoa post-harvest.

Regarding the values obtained for Mean Squared Error (MSE) in the trainings, values close to zero were expected; however, the results are far from this number. This can be explained as a result of the discontinuity and limited amount of experimental data. The implementation of Adrover's isothermal dehydration model is considered positive, as due to the limited amount of experimental data, approximately 2500 data points, there was a possibility of model non-convergence, which would have been evidenced as a negative result or very close to zero in the coefficient of determination, or the predictor would have simply returned a non-convergence error in the IDE used (PyCharm).

Despite the limited training data, the results achieved were seen as positive, demonstrating the effectiveness of convergence-accelerating algorithms [14]. Future research should incorporate genetic variability of the cocoa seeds used, as this influences both physical and microbiological characteristics [14, 33].

IV. CONCLUSION

A post-harvest cocoa condition predictor has been implemented, focusing on internal moisture content. This system utilizes an artificial neural network (MLP adjusted with backpropagation), developed using the Scikit-learn 1.4.1 library in Python 3. It can make predictions within a range of 0 to 420 hours, based on experimental results, with 70% of the data used for training and 30% for validation.

The predictor addresses the variability of temperature in the post-harvest process through machine learning, making it applicable to artisanal or traditional cocoa processing farms. From the integration of experimental data, the model shows a mean squared error (MSE) of 153 and a coefficient of determination R^2 of 0.82, indicating the need for more data to achieve lower MSE and higher R^2 values.

The use of convergence functions, such as the isothermal dehydration model by Adrover et al. (2020) and the Brusselator model, allows for convergent results in fewer iterations, especially with a small experimental database. The primary output of the predictor is the internal moisture of the seed at any point during post-harvest, while outputs like pH and volume provide additional validation. Future research should include a variable representing the genetic diversity of the cocoa lot to enhance prediction accuracy as the database grows

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