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Abstract

This study compares three machine learning (ML) models -artificial neural networks (ANN), recurrent neural networks (RNN), and extreme gradient boosting (XGBoost)- for predicting the drying kinetics of wood biomass from the clearing of outdated apple and apricot orchards. The primary goal was to optimize and evaluate the performance of these models in predicting drying time and moisture content of the wood, which is crucial for improving energy efficiency in the drying process. Experiments were conducted under four temperature regimes (40°C, 50°C, 60°C, and 70°C) to simulate low- and high-temperature drying conditions. The models were trained and evaluated using statistical quality metrics such as root mean squared error (RMSE), mean absolute error MAE, and R^2. Results showed that all models performed with high accuracy, but XGBoost demonstrated the best statistical performance, exhibiting the lowest MAE and RMSE values. The RNN model exhibited the highest R^2 values and performed well in terms of MAE and RMSE, whereas the ANN model yielded slightly lower results. Despite small differences in performance, the models showed strong predictive capabilities and can be effectively used for modeling the drying process of moist wood biomass. This research emphasizes the significance of model optimization in enhancing the accuracy of drying time predictions and minimizing energy consumption in drying processes.

Key words: artificial neural networks; recurrent neural networks; XGBoost; wood drying.

Introduction

Rational energy management with the use of renewable energy sources has become imperative in recent decades in order to achieve sustainable development and environmental protection. The uncontrolled depletion of fossil energy sources has made the effects of greenhouse gases more pronounced, and climate change more intense. In order to mitigate the negative environmental impacts, renewable sources are expected to take over two-thirds of the total energy consumption and 86% of power generation in the global energy transition in the coming years (IRENA, 2019). In transition countries and EU candidate countries, such as the Republic of Serbia, the household sector has the greatest potential to reduce energy consumption and increase the use of renewable energy sources, given that it traditionally relies on biomass for heating and cooking (Gonzalez-Salazar *et al.*, 2014). According to data from the European Commission, for years, around 63% of total energy consumption in households goes to heating, where renewable energy sources are represented by about 22% (Eurostat, 2024). In the Republic of Serbia, the situation is different, with firewood being the main fuel source, accounting for 47%, and together with pellets and other wood fuels, it reaches 50%. In households, the consumption of firewood is significantly higher, with a share of 77%, while in urban areas, where most are connected to the district heating system, this share is around 28%. Although firewood is an ecologically renewable energy source, environmentally friendly, easily accessible, and often a cheaper fuel compared to other sources, burning wood fuel can produce a significant amount of PM particles and CO_2, which, during the winter months, particularly in urban areas, causes high levels of air pollution (IEA, 2024). Maximum efficiency and reduction of particle and smoke emissions are achieved only by burning dry wood, which also has higher thermal power than wet wood and burns longer. Therefore, it is necessary to ensure dry wood for efficient combustion, which has been properly stored.

Due to its relatively low price on the market and easy availability, wood logs have been for decades the most common form of biomass used for heating, not only in the Republic of Serbia but also in other countries of the Western Balkans. The negative result of this positioning of wood logs on the energy market led, in the past decade, to the irrational and almost uncontrolled felling of forests. Serbia is considered a moderately forested country, in which forest biomass is the only type of biomass used for heating households, either in the form of wood logs or briquettes, chips, or pellets. This approach led to significantly reduced forest areas in the past decade. Fortunately, over the past ten years, the total forested area has increased from an estimated 2,645 million ha in 2012 to about 3,025 million ha, according to the Organization of Forestry in Serbia in 2023, which represents a 5% increase in forest land area (Derčan, 2012). Although there is significant potential in biomass generated as a result of fruit and vineyard production, unfortunately, it is rarely used. One of the main activities in fruit and vineyard production is pruning, which generates a significant amount of organic waste, about 50% of which could be used for heating and cooking (Ilic, 2024). On the other hand, there are a large number of old plantations, over 20 years old, which need to be cleared and replaced with new ones. According to data from the Statistical Office of the Republic of Serbia, in 2017, the area under the most important fruit varieties: apples, pears, peaches, apricots, and nectarines were 56.41 thousand ha, with a total of 66.02 million trees. Of that, 42% of the area was covered by outdated plantations with a fund of 48% of the total number of trees (Statistical Office of the Republic of Serbia, 2024). Since there is no organized treatment of the waste generated from clearing old plantations, farmers are forced to handle the waste themselves, which could most easily

be processed into wood chips, although this is the least used form for heating. The downside of wood chips is their relatively high moisture content, which can range from 20% to 30%, which, when burned, generates particles ranging from 8 to 30 PM. By drying this wood chips produced from old fruit plantations, it would become energy-efficient biomass suitable for heating, and at the same time, solving the waste problem would have a positive impact on environmental protection and sustainable development (Perić *et al*., 2020; Strehler, 2020).

Wood drying is a key operation in the wood industry and woodworking, which primarily aims to reduce the moisture content in the wood while maintaining its physical integrity and stability. Due to poorly managed drying processes, uneven moisture content can occur inside the wood, leading to shrinking, warping, and even cracking of samples. This topic has been studied for the last 30 years. From examining drying at low or high temperature regimes, significant observations have been made regarding the drying process of wood samples (Simpson, 1983a), to the application of some modern drying methods, such as freeze drying, superheated drying, supercritical CO_2 dewatering, vacuum drying, and others (Espinoza *et al*., 2016; Bovornset *et al*., 2007; Yang *et al*., 2020; Shaozhi *et al*., 2016, Elustondo *et al*., 2023). Research on the process is generally based on determining empirical dependencies between drying time and dimensionless moisture content in the material, which are often of an exponential nature.

The application of artificial intelligence (AI) in modeling drying processes in the food industry, especially artificial neural networks (ANN), has proven to be an accurate and reliable tool for predicting and studying drying processes. Various models and networks have been used to predict moisture content in materials or drying rates, based on experimental data sets, but based on image processing (Khan *et al*., 2022; Ropelewska *et al*., 2023; Aghbashlo *et al*., 2015; Martynenko *et al*., 2018). The specificity in the case of wood drying is predicting the specific cracks that may appear during the drying process, for which networks that predict based on image analysis have proven to be exceptionally good (Morales-Reyes, 2023; Ji *et al*., 2024; Tian *et al*., 2023). Based on the idea that wood biomass from clearing old orchards could be used to produce wood chips, and that drying can significantly reduce moisture content in the material, the goal of this work is to model the prediction of drying rate for two samples -apple and apricot- using ANN networks and determine the most reliable model. Drying rate is the data on which the total mass of dried wood can be estimated, and based on that, energy consumption during the drying process can be predicted. The networks used in this experiment are the classic ANN network, recurrent neural networks (RNN), as well as very precise extreme gradient boosting (XGBoost) networks that can process data of different categories. The quality of the networks was determined through classical statistical parameters, such as R^2, mean squared error (MSE), and root mean squared error (RMSE).

Materials and Methods

Preparation and drying of wood samples

The goal of the experimental part of the research was to determine the drying rate depending on the sample mass, current moisture ratio, drying temperature, and sample type. Unlike standard procedures in modeling the drying kinetics of biological materials, where the moisture ratio is determined as a function of drying time, the drying rate is a parameter that can later be used to

determine the total energy consumption during the drying process and evaluate the efficiency of the process relative to the increased thermal power of the wood biomass obtained after drying.
The samples were taken from three plantations of old apple and apricot orchards. Branches of the same diameter were first cut from the trees, and then disks with a diameter of 100 mm and thickness of 20 mm were formed in the laboratory, as shown in Figure 1. One sample of each wood type was taken to determine the initial moisture content by drying at 105°C.

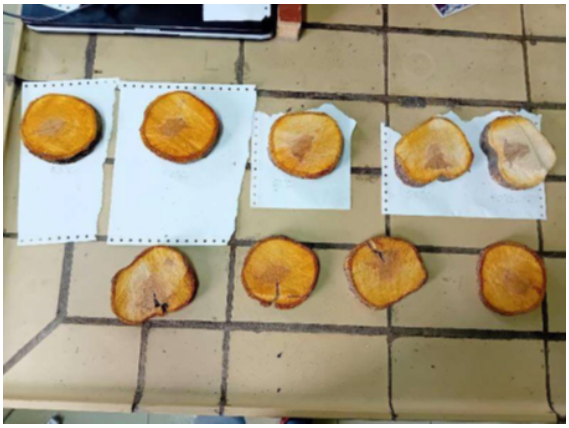


Figure 1. Wood discs samples for experimental drying process.

For all the samples, the drying conditions were set as follows: drying temperatures of 40°C, 50°C, 60°C, and 70°C, with an air flow speed of 2 m/s. The drying process was stopped once the equilibrium moisture content was reached, when the sample mass did not change between two measurements. The experiment was carried out in an experimental convective dryer that is fully automated, with a movable platform that automatically places the tray with samples on a scale at a predetermined time when the measurement is taken, without disturbing the air flow (Milanović *et al.*, 2022).
The sampling time was set at the beginning of the experiment, and an interval of 15 min was taken in all experiments, depending on the material type being tested.
The current moisture content in the drying material can be transformed into a dimensionless moisture content (Doymaz, 2012):

$$MR = \frac{M_t - M_e}{M_0 - M_e} \quad \text{(Eq. 1)}$$

Where M_t, M_0, and M_e are the moisture content at any time of drying, initial moisture content, and equilibrium moisture content (kg water/kg dry matter), respectively.
The drying rate (DR) (kg water/min) is calculated using the following equation (Lerman *et al.*, 2023).

$$DR = \frac{M_t - M_{t+\Delta t}}{\Delta t} \quad \text{(Eq. 2)}$$

The total energy consumption was empirically determined based on the drying conditions for given temperatures(Rajković *et al*., 2023):

$$Q_v = a \cdot \tau + b \quad \text{(Eq. 3)}$$

Where τ is the drying time (min), and the coefficients a and b are empirically determined.
The specific energy consumption q_{vq} (kJ/kgw) is determined based on the total energy consumed during drying and the total moisture evaporated during the process:

$$q_v = \frac{Q_v}{m_v} \quad \text{(Eq. 4)}$$

Application of artificial intelligence in the drying process

Deep learning (DL), as a subset of artificial intelligence, has recently emerged in academic community as a scientific discipline that learns from complex structures within large real-world data sets. Based on simulating the work of the human brain, DL models are designed for computers to learn from provided data and independently find patterns between input and output parameters, with the ability to adjust their current parameters to correctly calculate the output. Traditional machine learning techniques such as regression or classification have limited data processing capabilities in some complex structures. This is particularly evident when there are different types of dependencies between output and input variables. On the other hand, the multiple layers between input and output data in DL models provide the possibility to transform the representation at a lower level to a higher level (Alsheikh *et al*., 2016; Arel *et al*., 2010; Samsonovich, 2020; Ryan *et al*., 2020). In this way, DL models offer endless possibilities for forming complex models that can represent processes such as drying in a qualitatively different manner.
In the traditional way of determining the drying kinetics of wet materials, only the empirical dependency of dimensionless moisture ratio as a function of drying time is determined. Although other drying parameters are indirectly incorporated into these values, there is no possibility to observe the direct dependency, for example, of temperature or air flow rate on the drying process. On the other hand, DL models can link such quantities into models that will have dimensionless moisture ratio as an output, or even multiple output parameters.
The most commonly used ANN, based on the structure of biological networks in the brain, consist of a large number of basic units—artificial neurons that are interconnected through weights, which are analogous to synapses. The ANN model learns by adjusting the weights through its layers. The simplest model consists of three layers: an input layer, a "hidden layer," and an output layer (Keskes *et al*., 2020; Haykin, 1999). For better model precision, input data are normalized within the range between 0 and 1. The output layer contains the corresponding number of output parameters that the model must predict. The number of hidden layers and the number of neurons within them depends on the complexity of the model and the problem being solved. These values are determined through a corresponding number of model simulations, along with model hyperparameters, to achieve the final model that provides the highest accuracy. ANNs have been successfully applied in drying processes, depending on whether they confirm the empirical relationship between moisture ratio and drying time or in more complex models where dependencies such as drying temperature, air

flow rate, geometry, and material physical characteristics are examined (Kırbaşa *et al*., 2019; Xiao *et al*., 2010; Ghaderi *et al*., 2012; Złotek *et al*., 2019; Zhang *et al*., 2014).

Recurrent neural networks (RNNs) are more complex models than ANNs. The advantage of these models is that they "learn" from previous layers. In ANN models, it can be assumed that the input and output data are independent of each other, as is the case in image detection applications. RNNs save the output of a layer and feed this output back into the input to better predict the outcome of the layer. The first layer in the RNN is quite similar to the feed-forward neural network, and the recurrent neural network starts once the output of the first layer is computed. After this layer, each unit will remember some information from the previous step so that it can act as a memory cell in performing computations (Günaydına *et al*., 2014; Li *et al*., 2022).

Extreme gradient boosting (XGBoost) belongs to ensemble learning techniques, which iteratively passes through an ensemble of weak learners, usually with decision trees, to eventually generate a strong prediction model. The advantages of XGBoost models are high flexibility, strong predictive ability, high scalability, and high learning efficiency. These models have proven to be extremely successful in processing different types of data in both regression and classification models, as they use regularization to minimize the loss function. XGBoost models progressively correct prediction errors, using approximations through decision trees. The success of these networks lies in their ability to adapt to a wide range of applications. The current application of these models can be direct, through integration with other algorithms, and parameter optimization (Sagi *et al*., 2011).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad \text{(Eq. 5)}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \quad \text{(Eq. 6)}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\left[\frac{(\hat{y}_i - y_i{}^2)}{n}\right]} \quad \text{(Eq. 7)}$$

The goal of this research is to apply ANN, RNN, and XGBoost models in predicting the drying rate of wood samples. In all models, the same input parameters were set: drying time, dimensionless moisture ratio, drying temperature, and sample type, with one output parameter. The choice of appropriate ANN and RNN networks was determined by optimizing the number of hidden layers, the number of neurons in the layers, and adjusting the hyperparameters, learning rate, and epochs, as well as the activation function in the ANN model. The XGBoost regression model was optimized according to its parameters: booster, learning rate, and objective. The model selection and final comparison of model efficiency were based on standard statistical metrics, such as the coefficient of determination, mean absolute error, and mean square error.

Results and Discussion

Experimental drying of wood disks

The mass change of the material was recorded every 15 minutes using a balance placed under the drying chamber. The balance used was Kernel (Kernel S232) with an accuracy of ±0.01 g. The hot air temperature was measured and regulated by the PID temperature controller (REX C-100) with an accuracy of ±0.1°C, and the thermocouple also had an accuracy of ±0.1°C. Air velocity was adjusted with a frequency regulator attached to a fan, set at 2 m/s for all temperature regimes. The air velocity was verified using the hot wire anemometer AirflowTM TA35, with an accuracy of ±0.05 m/s. The temperatures of the hot air during the drying process ranged between 50°C and 70°C. The experiments are numbered as shown in Table 1, detailing the drying time and parameters.

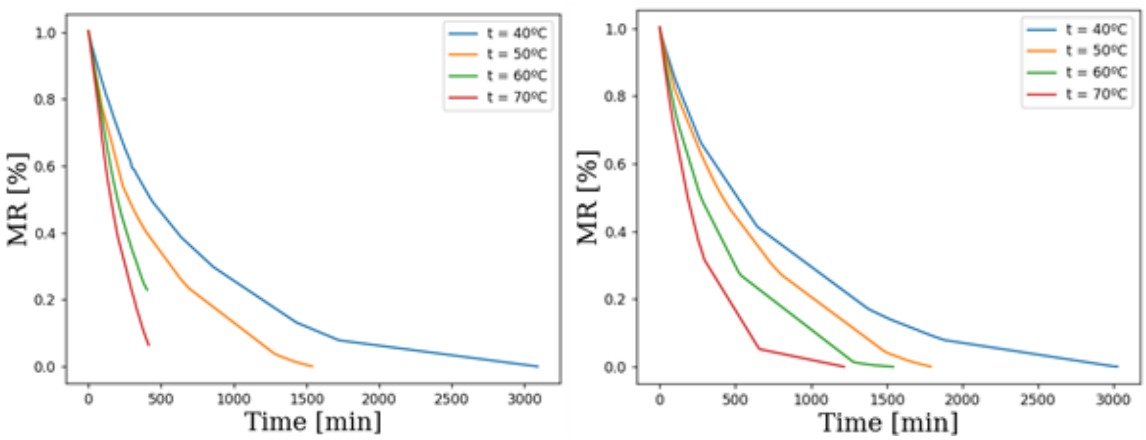
Table 1. List of performed drying experiments.

Experiment	Temperature (°C)	Wood type	Drying time (min)
E400	40	Apple	3086
E500	50	Apple	1540
E600	60	Apple	414
E700	70	Apple	404
E401	40	Apricot	3025
E501	50	Apricot	1791
E601	60	Apricot	1543
E701	70	Apricot	1228

The moisture ratio-time drying curves, shown in Figure 2, depend on the temperature and the type of wood used for drying.

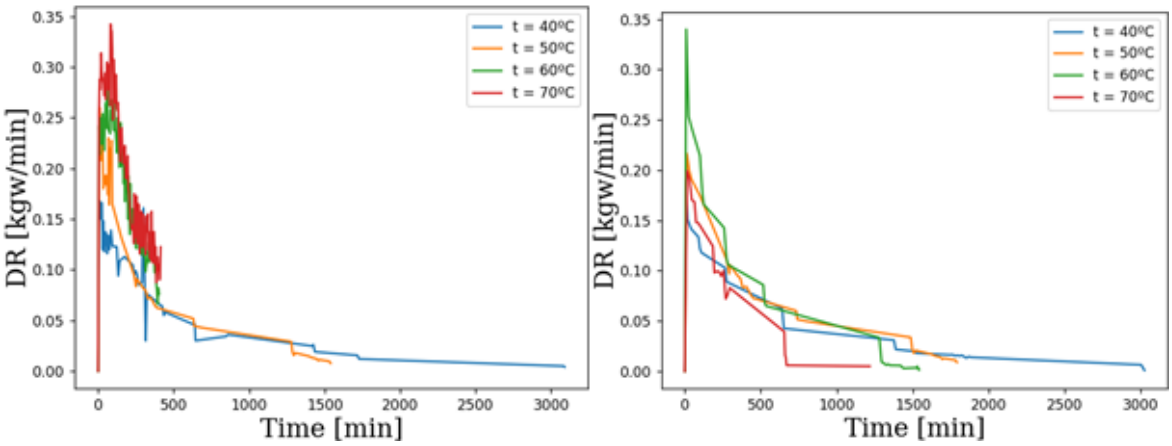
Except for the 40°C temperature, where the drying of apricot was slightly faster, in all other experiments the drying time for apricot was longer. Apple wood performed excellently at higher temperatures, showing a noticeable reduction in drying time. The nature of all curves followed an exponential trend, which corresponds to the general drying kinetics of moist biological materials. In standard procedures for determining drying kinetics, all curves could easily be approximated using known empirical equations.

Figure 3 shows the change in drying rate relative to drying time for both materials at various temperature regimes. The drying rate for apple showed more fluctuation across all regimes, whereas for temperatures of 40°C and 50°C, the drying rate followed a stable curve that asymptotically decreased. For apricot, fluctuations were less pronounced, but the diagrams clearly indicated a pattern relative to all temperature regimes.



a) b)

Figure 2. Moisture ratio (MR) – time drying curves depending on airflow speed: a) apple tree, b) apricot tree.



a) b)

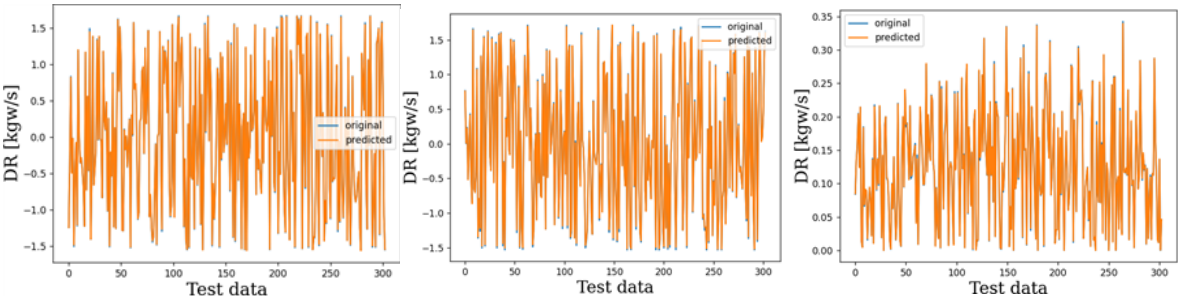
Figure 3. Drying rate (DR) – time drying curves depending on airflow speed: a) apple tree, b) apricot tree.

Selected models

Through the optimization of the ANN model, a model with two hidden layers, each containing 50 neurons, was selected. The activation function used was "tanh," the Adam optimizer was applied, and the learning rate was set to 0.004. The total number of parameters in the network was 8705, of which 2901 were trainable, and 5804 were optimizer parameters.

The best RNN model had three hidden layers with 15 neurons in each layer. Like the previous model, "tanh" was used as the activation function, the Adam optimizer was chosen, and the learning rate

was set to 0.0013. The total number of parameters in the network was 3605, with 1201 trainable parameters and 2404 optimizer parameters.
Since this was a regression task, the XGBoost regression model was selected, with the "gbtree" booster parameter, "linear" objective, and a learning rate of 0.1. Considering that this research compared the three best models from different machine learning techniques, all models demonstrated statistically excellent results, as shown in Figures 4 and 5.



a) b) c)

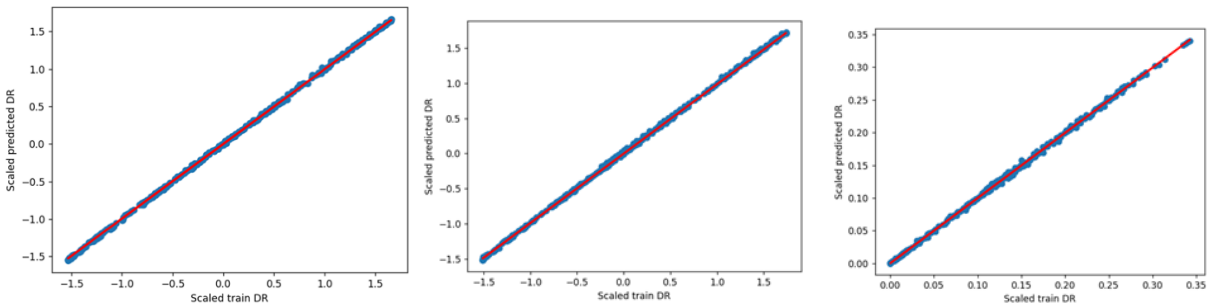
Figure 4. Comparison of actual and model-predicted data.

As seen in Figure 4, each model demonstrated high accuracy, with the graphical representation of actual and predicted data almost overlapping. From the graphical display alone, it is not possible to determine which model performed best, so statistical methods, shown in Table 2, were used.

Table 2. Variation of RMSE, MAE, and R^2 values for different ML models.

Model	R2	MAE	RMSE
ANN	0.9999124	8.7587024e-05	0.009358793
RNN	0.9999470	5.2956892e-05	0.007277149
XGBoost	0.9995050	3.4891743e-06	0.001867933

According to the statistical indicators, the XGBoost model had the lowest values for mean absolute error (MAE) and root mean square error (RMSE), with a 96.01% lower MAE and an 80% lower RMSE compared to the ANN model, and a 34% lower MAE and 74.3% lower RMSE compared to the RNN model. These are very small differences, considering that all three models showed high R^2 values, and MAE and RMSE were minimized. However, it can be concluded that XGBoost is slightly better. The RNN model had the highest R^2 value and performed 39.5% better in terms of MAE and 22% better in terms of RMSE compared to the ANN model.



a) b) c)

Figure 5. Actual drying rate data *versus*: a) ANN model predicted data, b) RNN model predicted data and c) AXGBoost model predicted data.

Another indicator of the good training of the models is the dependency between actual and predicted values for all three models, shown in Figure 5. All three models demonstrate exceptional alignment, with no data points deviating from the true line for the validation data (Table 2).

Figure 6. Correlation matrix between input data.

The significance of optimizing ML models by varying hyperparameters is substantial, especially when the data is not highly correlated or exhibits a negative correlation, as is the case with the data used in the models examined (Figure 6).

Almost all the data have a negative correlation with each other, which explains the choice of "tanh" as the activation function. Parameters that do not enter the empirical equations for drying kinetics, such as temperature and material type, have low correlation indices compared to the highly

correlated time, mass, and dimensionless moisture ratio. Drying time is just one interpretation of the drying kinetics, and it has been previously shown that the shape of the curves is similar to that of the moisture ratio (MR).

The quality of an ML model can also be presented using a confusion matrix (Figure 7). The confusion matrix is a standard procedure for performance measurement in machine learning classification. In cases where it is not a binary classification, as in the models under study, the actual and predicted data can be normalized to obtain the confusion matrix. The confusion matrix is a two-dimensional matrix with four elements: TP – true positive, TN – true negative, FP – false positive, and FN – false negative. Depending on how the model makes predictions, the quality metrics for the confusion matrix are as follows:

- **Accuracy** – the proportion of correctly classified objects in the total number of objects.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{(Eq. 8)}$$

- **Precision** – the proportion of true positive predictions out of all positive predictions made by the model.

$$Precision = \frac{TP}{TP+FP} \quad \text{(Eq. 9)}$$

- **Recall** – the proportion of true positive predictions made by the model out of all actual positive samples in the dataset.

$$Recall = \frac{TP}{TP+FN} \quad \text{(Eq. 10)}$$

a) b) c)

Figure 7. Confusion matrix for: a) ANN model, b) RNN model and c) XGBoost model.

There were no significant deviations in the quality metrics values, as seen in Table 3, and it can be concluded that based on the slightly better overall prediction accuracy, the ANN model appears to be superior to the others. In this case, however, the XGBoost model provided the worst results, as it had the highest percentage of false positive and false negative values.

Table 3. Confusion matrix quality metrics.

Model	Accuracy	Recall	Precision
ANN	0.9900	0.9956	0.9898
RNN	0.9770	0.9714	0.9956
XGBoost	0.9870	0.9700	0.9908

Conclusions

The aim of this research was to compare three machine learning models that can generally be used for modeling the drying of moist materials, in this case, wood from the clearing of outdated apple and apricot orchards. Assuming that such wood, with a high moisture content exceeding 30%, is not suitable for further processing, the only acceptable option is to produce wood chips, which would be dried to specified moisture content, thereby increasing their calorific value. Drying rate is a measure that can indicate how the wood will dry, allowing for the determination of drying time for a given amount of moist material and, consequently, the total amount of energy needed to reduce moisture content to the required level.

The material was dried under four temperature regimes, where temperatures of 40°C and 50°C should correspond to low-temperature drying (e.g., in solar dryers), without solar radiation conversion, and temperatures of 60°C and 70°C correspond to high-temperature drying, but using a renewable energy source for enhanced energy efficiency.

The formation of ML models does not explicitly require knowledge of the studied domain, but later optimization processes are essential to identify dependencies between input and output variables. Machine learning models have become attractive in recent years because they can predict values with high accuracy. It is important to consider the type of ML model, whether it is general classification or regression, as these can often be very similar due to the data used.

The example in the paper shows that frequently chosen models, such as ANN, RNN, and XGBoost, can be optimized to make accurate predictions. It is important to note that when optimizing the model, care must be taken to ensure that the statistical quality metrics provide the best results. This is often a long and tedious process, especially considering all the parameters that may change in a model. Although the optimizations of the models are not detailed in this paper due to the large amount of data, varying several hyperparameters results in a wide range of solutions. Models later analyzed match the initial characteristics of their respective groups. The RNN model, compared to the ANN model, has far fewer parameters that need to be trained, and always shows better accuracy than the ANN model, as seen in the results, where the RNN model is about 30% more accurate according to statistical quality metrics.

In contrast to these two models, XGBoost, with its ability to adjust decision trees iteratively, provided the best statistical quality metrics. However, the confusion matrix, as one of the quality metrics, can also serve as a good indicator of the quality of an ML model. When data normalization is performed, formalizing each ML model to binary regression, the ANN model showed the best characteristics. All models showed almost no deviation in predicted values, but XGBoost had worse results in terms of accuracy compared to the other two models. The RNN model performed better in the middle range according to the confusion matrix quality metrics. When considering all the factors in this study, the RNN model was the best, followed by XGBoost and lastly ANN, with very small and practically negligible differences. Therefore, it can be concluded that the presented models can be used efficiently for predictions in drying wood biomass.

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