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Predictive Analysis in Solar Kiln Drying of Wood using Recurrent Neural Networks

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ABSTRACT
Prediction in data mining, is a technique used in predicting results or outcomes of future occurrence in reference to existing information. Several predictive models have been developed for different fields of study. In solar kiln drying experiment, as a result of dependence on nature for its operation, outcomes of drying process is unstable and varies with weather variability. Although predictive models have been developed for wood drying experiments, there is very limited information on the use of Neural Networks for predicting outcomes in solar kiln drying of wood. In this work, Long Short-term Memory model, a special type of Recurrent Neural Network was adopted for prediction in solar kiln drying of wood. Data collected on external (atmospheric) and internal conditions of a solar kiln sited at from Forestry Research Institute of Nigeria was used for this study. Daily ambient and internal temperature and relative humidity were used as input data. The closeness of relationship between the experimental and predicted values (Mean Square Error, MSE = 0.97; 30.4) and (Squared Correlation, R2=0.68, 0.85) for Temperature and Relative Humidity respectively revealed that the model had a good agreement with data. The Equilibrium Moisture Content (EMC) of internal solar kiln environment which influences the outcome of drying was considered. The EMC of internal solar kiln environment was predicted for the next 730 days and suitability of the model for prediction was examined giving an MSE value of 0.2 and r2 value of 0.87. The findings of this study suggest a viable model for predicting drying outcomes under varying weather conditions.

General Terms
Prediction

Keywords
Equilibrium Moisture Content, Long Short-term Memory, temperature

1. INTRODUCTION
Prediction is the act of forecasting future occurrence. Specifically, in data mining, prediction is a technique in which outcomes of future event are predicted. It results into output of an algorithm after being trained on a historical dataset and applied to new data when forecasting the likelihood of a particular outcome. Prediction is a very essential phenomenon which is adopted in order to forecast into the future upfront (Janssens, 2018). Predictive Models are expressions or equations which are applied for the purpose of explaining or analysing a concept. They are tools that facilitate the understanding of a phenomenon in any field of study. Basically, models are developed and can be used to assist in understanding and communicating about a system or concept of interest with the aim of bringing a positive improvement to how such a concept was ordinarily addressed (Rathod and Valmik, 2014).

2. RELATED WORKS
Several predictive models have been developed and used for analysis in different fields of study such as geography, meteorology, political science, education studies, forestry, fisheries, wood science, medical studies, just to mention a few. Reports revealed that predictive models are essential tools in data mining which have proven to assist in making critical and relevant decisions related to the identified field. Especially, when such models are properly designed and thoroughly validated with appropriate statistical study (Chai et al., 2018; Janssens, 2018; Ghorbani and Ghousi, 2019).

Wen, et al. (2012) proposed a moisture content predictive method for wood drying process using non-linear model-based SVM. The authors analysed the properties of moisture content (MC) during wood drying showing that MC is determined by drying temperature and equilibrium MC, also that wood consists of free and bound water. The model predicted moisture content of wood drying process including free and bound moisture content. However, this study did not include Relative Humidity in its parameters which is also very important in determining the EMC of wood.

Zhang et al. (2006) developed the Time-delay neural network (TDNN)-based temperature-humidity system of wood drying with the identification structures of TDNN network given. Their work separately presented the control and the schedule model, which shows the relationship between control signal and temperature-humidity and also shows the relationship between moisture content of the wood and temperature-humidity of wood drying. The simulation of the models were done by the use of the measured data obtained from the experimental kiln dryer. From the simulation results, it could be observed that the method of modelling was feasible, and the models were found to be effective.

A study by Zhu et al (2009) reveals the vibration features of wood. An ANN model was developed by exploring the wavelet analysis and the ANN for the defects of wood composite materials on the basis of non-destructive testing. This model was established for non-destructive testing technology of wood-based composite materials. Wu and Avramidis (2006), in their work, applied ANN techniques in predicting drying rates of timber kiln based on the wood species and the information on basic density for the hem-fir mix which are found along local coastal areas. The ANN models developed predicted a single output which is the average final moisture content using the following as inputs: initial wood moisture content, basic density of the wood, and drying time of the wood.

Zanuncio, et al (2016) used ANN to determine and study the wood MC in the process of drying. After the samples were saturated, followed by evaluation of drying until EMC was reached, the ANNs were created. The materials with higher initial MC reached EMC faster due to their higher drying rate. The basic density of the wood samples was indirectly proportional at the onset and exactly proportional to the moisture by the end of the drying process. The ANNs showed high level accuracy in estimating the moisture content, however, the neural network built using the basic density as well as number of days of drying became the best. They conclusively found ANN to be useful in control the MC of wood in the process of drying.

Ojo and Adeyemo (2013) used Artificial Neural Networks (ANN) model for prediction using one hidden layer and three processing elements in the ANN model. Regression Analysis model was also used. Prediction was done using regression analysis. The parameters of regression model were estimated using Least Square method. To determine the better prediction, mean square errors (MSE) attached to ANN and regression models were used. Seven real series were fitted and predicted with in both models. It was found out that the mean square error attached to ANN model was smaller than regression model which made ANN a better model in prediction.

In Ojo (2017), Neural Networks model was used in the prediction of abstracts from The Institute of Electrical and Electronics Engineers (IEEE) Transactions on Computers. Simulation of results was done using the Polynomial Neural Networks algorithm. This algorithm, which is based on Group Method of Data Handling (GMDH) method, utilizes a class of polynomials such as linear, quadratic and modified quadratic. The prediction was done for a period of twenty-four months using a predictive model of three layers and two coefficients. The performance measures used in this study were mean square errors, mean absolute error and root mean square error.

3. METHODOLOGY

3.1 Data Collection

Data set used for this study was obtained from Forestry Research Institute of Nigeria. The data which is in two parts, contains 7,379 records of meteorological data from meteorological station of the institute and another data consisting of a daily record of the drying factors and the EMC in the solar wood drying chamber (kiln) for 1,018 days taken from the Forest Products and Utilization department of the institute.

3.2 Data Preparation

Many application areas of artificial intelligence, like pattern recognition, machine learning and data mining require that the dataset be prepared through pre-processing the raw data in order to have a quality data. The data to be used as input for data mining algorithms is assumed to be rightly distributed, not containing missing or incorrect values with all features seen as important. In the real-world, given data may be incomplete, noisy, and inconsistent. This can make useful patterns hide or disguise. Data preparation, which is known to be a first major step in the data mining process and has a great part to play in the entire data mining process because it requires processing of the original data to make it fit to a specific data mining task.

ANNs are capable of handling numerical data. The representation of the attributes of a learning problem in a neural network plays a great part in influencing the quality of the solutions that can be obtained. Based on the nature of the problem, several kinds of attributes are to be represented. Each of these attribute types has corresponding reasonable methods of neural network representation. We will now discuss each attribute kind and some common methods to represent such an attribute:

Real-valued attributes are usually mapped into the range 0…1 or −1…1 through rescaling using some function in a way that makes an even distribution within the given range.

For *Integer-valued attributes*, datasets are usually handled as though they were real-valued. When number of different values is only small, one of the representations can be used for ordinal attributes. It should be noted that attributes whose values are integer numbers are not really integer-valued but are ordinal or cardinal instead. All integer-valued attributes are considered as real-valued.

Ordinal attributes which have m different values can be mapped to an equidistant scale which makes them false real-values or represented by m −1 inputs in which the leftmost value k has value of 1 to represent the kth attribute value while the rest are 0. Binary codes using log2 m inputs can also be used.

Nominal attributes having m different values usually are represented using a 1-of-m code or by a binary code.

Missing attribute values can be replaced by a fixed value (e.g., the mean of the non-missing values of this attribute) or can be represented explicitly by adding another input for the attribute that is 1 if the attribute value is missing.

For this study, the data is void of noisy records while the missing values were handled by imputing the mean of the non-missing values of the missing attribute values at random.

3.3 Predictive Model Formation

3.3.1 Regression Model for environmental conditions

This is the first stage of forming the models. Here, RapidMiner Studio was used to conduct regression analysis in order to assess the relationship between Ambient and Solar weather conditions (Temperature and Relative Humidity). This was done in order to determine the dependence of solar kiln condition on the atmospheric condition at any particular point in time.

3.3.2 Predicting the Ambient weather conditions

For this phase, the Long Short-Term Memory (LSTM) neural network was used. Specifically, the stacked LSTM consisting 2 layers was employed. A typical LSTM network is made up of memory blocks usually known as cells. A cell accepts two states from its preceding cell: the cell state and the hidden state. The cell state, the main chain of data flow, allows the data to flow forward without being tampered with. Certain linear transformations may however, occur. The data being conveyed by the cell state can either be added to or removed from it through the sigmoid gates. A sigmoid gate looks like a layer or a series of matrix operations, containing a number of individual weights. LSTMs use the gates to control memorizing process which help them to overcome the long-term dependency problems.

In constructing an LSTM network, non-useful information is identified and omitted from the cell in the first step. This process is decided by the sigmoid function, where it takes the output of the last LSTM unit (h_{t-1}) at time t−1 and the current input (X_t) at time t, followed by the determination of which part from the old output should be eliminated. The gate is called the forget gate f_t; where f_t is a vector with values ranging from 0 to 1, corresponding to each number in the cell state, C_{t-1}.

$$f_t = \sigma\left(W_f[h_{t-1}, X_t] + b_f\right) \quad (1)$$

σ is the sigmoid function, while W_f and b_f are the weight matrices and bias, respectively, of the forget gate.

The next step is to decide and store information from the new input (X_t) in the cell state and to update the cell state. Here, we have two layers, the sigmoid layer and the *tanh* layer. The sigmoid layer is to decide if the new information should be updated or ignored (i.e 0 or 1), while the *tanh* function is to allocate weights to the values which are passed thereby deciding their level of importance (−1 to 1). These two values are then multiplied to update the new cell state. The resulting memory is then added to old memory C_{t-1} resulting in C_t .

$$i_t = \sigma(W_i[h_{t-1}, X_t] + b_i), \quad (2)$$

$$N_t = \tan h(W_n[h_{t-1}, X_t] + b_n), \quad (3)$$

$$C_t = C_{t-1}f_t + N_t i_t \quad (4)$$

In Equations 2, 3, and 4 above, C_{t-1} and C_t are the cell states at time t – 1 and t, while W and b are the weight matrices and bias, respectively, of the cell state.

Finally, the output values (h_t) are based on the output cell state (O_t) though now a filtered version. It should be noted that firstly, a sigmoid layer determines which parts of the cell state make it to the output of the sigmoid gate (O_t) which is then multiplied by the new values created by the tanh layer from the cell state (C_t), with a value ranging between −1 and 1.

$$O_t = \sigma(W_o[h_{t-1}, X_t] + b_o), \quad (5)$$

$$h_t = O_t \tan h(C_t). \quad (6)$$

Where W_o and b_o are the weight matrices and bias, respectively, of the output gate.

3.3.3 Model Structure

This study which is closely related to open-source software libraries. It was carried out using Python programming language. In addition, NumPy, Pandas, Matplotlib, keras, scipy libraries were imported for processing, management and visualization data. An LSTM model based on TensorFlow; an open-source software library provided by Google was developed. TensorFlow is according to original plans, used to conduct research on machine learning, deep learning, and numerical computation using data flow graphs. However, it is found to be sufficiently comprehensive to be applicable to a wide variety of fields.

This study, proposes a simple and effective model for predicting the weather drying conditions of solar kiln-dried wood, the characteristics of the input data were also of great concern because of their effects on the performance of the resulting model. These features include the input datatype, the amount of input data, and the correlation of the measured data. The input data included the average temperature and relative humidity for each day. The measured time series spans over 10 years, from 1999 to 2019. Two different combinations of inputs were proposed which are predicting ambient Temperature and Relative Humidity for 1,490 days, then the result of the prediction was then used to further predict Temperature and Relative Humidity in the solar kiln with respect to the regression model which was initially developed in the previous step of this study. This flow of activities in the model is shown in Fig. 1.

3.4 Predicting EMC

LSTM was used to develop a model for predicting the EMC and the input data for this include Temperature and Relative Humidity for both the ambient and in the solar kiln and the measured EMC all recorded at the same period of time. At this stage of the work, the resulting dataset from the previous step was used to predict EMC for the next 890 days as was done in the case of the prediction of ambient Temperature and Relative Humidity.

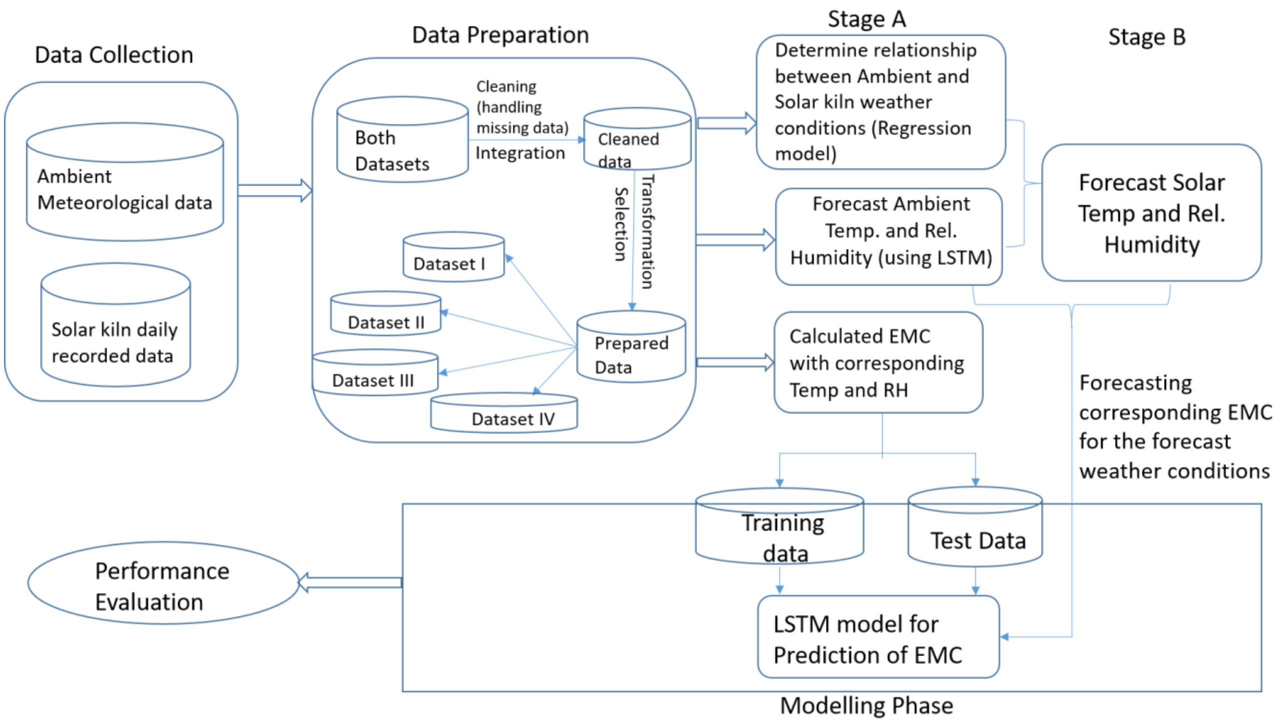

Fig 1: Model Structure

4. RESULTS PRESENTATION AND DISCUSSIONS

This section discusses the results of the research carried out using LSTM. Environmental factors which are related to wood drying were predicted using available data.

Table 1: Model Summary of Regression analysis for Relative Humidity

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.563[a]	.317	.316	3.82396

a. Predictors: (Constant), R H AMBIENT, TEMP. AMBIENT

Table 2: ANOVA of Regression analysis for Relative Humidity

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	87466.360	2	43733.180	312.967	.000^*
	Residual	141833.341	1015	139.737		
	Total	229299.701	1017			

a. Dependent Variable: RELATV HUMIDITY SOLAR

b. Predictors: (Constant), RELATV HUMIDITY AMBIENT, TEMP. AMBIENT

Solar RH.=46.132-1.516amb. temp +0.543amb. RH (R^2=0.317 or 31.7.1%; SEE=3.82396) (7)

Table 3: Model Summary of Regression analysis for Temperature

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.618[a]	.381	.380	11.82105

a.Predictors: (Constant), RELATV HUMIDITY AMBIENT, TEMP. AMBIENT

Table 4: ANOVA of Regression analysis for Temperature

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6887.674	2	3443.83	235.513	.000*
	Residual	4842.022	1015	14.623		
	Total	21729.696	1017			

a. Dependent Variable: TEMP. SOLAR

b. Predictors: (Constant), RELATV HUMIDITY AMBIENT, TEMP. AMBIENT

Solar Temp. = 34.698 + 0.494amb. temp – 0.143amb. RH (R2=0.381 or 38.1%; SEE=11.82105) (8)

Equations 7 and 8 are results of regression analysis for Relative Humidity and Temperature respectively. The fit statistics of models summarized in Equation 7 revealed that a unit increase in ambient temperature resulted to about 1.516times increase in solar RH while a unit increase in ambient relative humidity resulted to about 0.543 times increase in solar RH. Also, the result implied that about 31.7% of the variation in solar temperature can be explained by ambient temperature and relative humidity (Table 1). The ANOVA in Table 2 revealed that the model was significant at $p \leq 0.05$. This indicates that a significant relationship existed between the dependent (solar RH.) and independent (amb. T and RH) variables.

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The fit statistics of models summarized in Equation 8 revealed that a unit increase in ambient temperature resulted to about 0.494 times increase in solar T while a unit increase in ambient relative humidity resulted to about 0.143 times increase in solar temperature. Also, the result implied that about 38.1% of the variation in solar temperature can be explained by ambient temperature and relative humidity (Table 3). The ANOVA in Table 4 revealed that the model was significant at $p \leq 0.05$. This indicates that a significant relationship existed between the dependent (solar T.) and independent (amb. T and RH) variables.

4.1 Predicting the Ambient Environmental Condition

The environmental condition (Temperature and Relative Humidity) of the atmosphere around solar kiln chamber was predicted using LSTM. This implied that the expected external condition of the study area where the solar kiln was located for wood drying at any time of the year was predicted.

Figures 2, 3, 4 and 5 revealed the suitability of the model for predicting Ambient Temperature and Relative Humidity respectively.

Considering the closeness of relationship between the experimental and predict values (Mean Square Error, MSE = 0.97; 30.4) and (Squared Correlation, R^2=0.68, 0.85) for Temperature and Relative Humidity respectively, it can be said that the model had a good agreement with data.

4.2 Predict of Solar Kiln Environmental Conditions

In predicting the expected drying factors or solar internal condition for wood drying, a regression model was developed. This model was used to build a relationship between ambient environmental condition and internal solar condition. Data on measured Temperature and Relative Humidity for both Ambient and in the solar kiln was used for the regression analysis.

The predicted ambient temperature and relative humidity were inputted into the regression model to compute the temperature and relative humidity in the solar kiln.

The squared correlation (R^2) for Temperature was found to be 0.293 while that of RH was 0.373. The result of the regression analysis reveals that the model was significant. This implies that the dependent variables (Solar Temp and RH) were influenced by the independent variables (Amb Temp and Amb RH).

4.3 Prediction of Equilibrium Moisture Content (EMC)

The expected Equilibrium Moisture content of the solar internal condition was predicted using LSTM. The predicted EMC determines the expected moisture content of wood dried in the solar kiln at a particular period of the year. This implies that if given enough time, the moisture content of any wood dried in the solar kiln will reach an equilibrium with surrounding environment. However, this depends on the properties and previous moisture content of the wood species dried in the solar kiln. Data on predicted Temperature and RH with calculated EMC was used to predict EMC for the next 890 days.

Figure 6 reveals the suitability of the model for predicting EMC for a period of 890 days. The values of MSE (0.2) and R2 (0.87) reveals that LSTM-predicted values fits well into the calculated value of the existing EMC model.

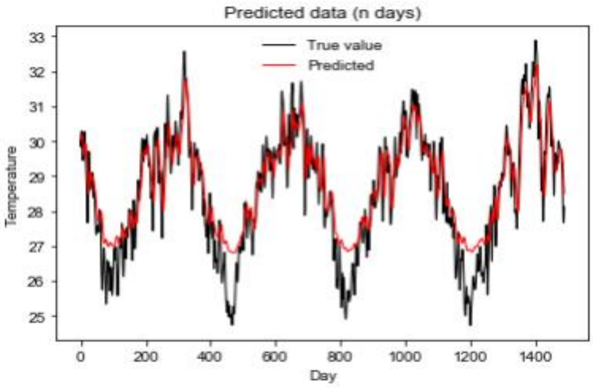

Fig 2: LSTM-Predicted and measured Temperature (Ambient)

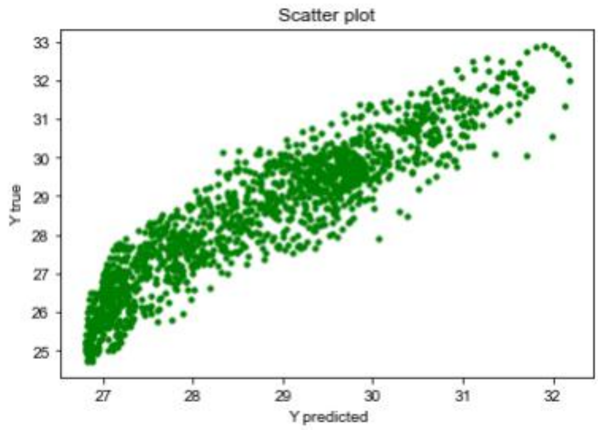

Fig 3: Scatter plot for predicted Ambient Temperature

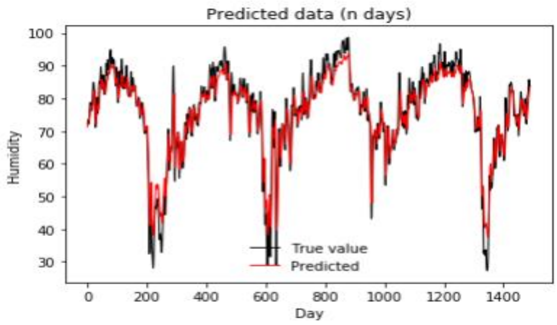

Fig 4: LSTM-Predicted and measured Relative Humidity (Ambient)

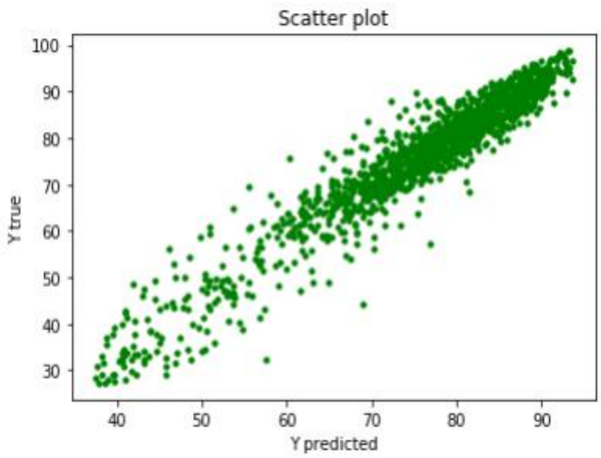

Fig 5: Scatter Plot-Predicted Ambient RH

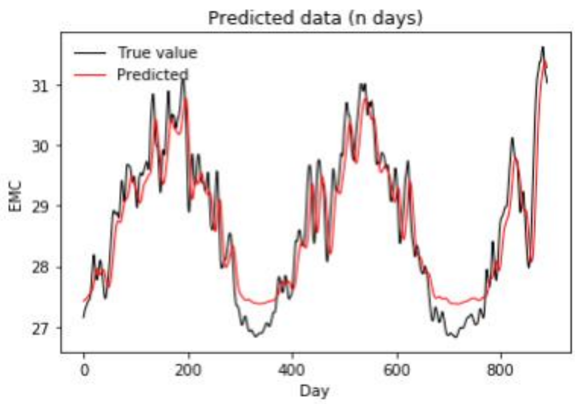

Fig 6: LSTM-Predicted and calculated EMC

6 CONCLUSION

In this study, an LSTM model used to predict EMC was developed. The findings of this study reveal the possibility of using LSTM for predicting drying outcomes under varying weather conditions. It was observed that the developed model was suitable because it fits closely to the calculated EMC. The coefficient of determination and MSE were used to evaluate the performance of the developed model. The closeness between the existing model (Hailwood and Horrobin) and the LSTM model developed in this work is an indicator that the latter was appropriate for predictions in wood drying processes.

7. ACKNOWLEDGMENTS

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8. REFERENCES

[1] Dipeeka K. Rathod and Neha Valmik (2014). Overview of Data Mining Techniques. *Advances in Computer Science and Information Technology (ACSIT)* Print ISSN: 2393-9907; Online ISSN: 2393-9915; Volume 1, Number 2; November, 2014 pp. 74-76 © Krishi Sanskriti Publications http://www.krishisanskriti.org/acsit.html

[2] Ghorbani, R and Ghousi, R. (2019). Predictive Data Mining Approach in Medical Diagnosis: A review of some diseases' prediction. *International journal of Data and Network Science* 3:47-70

[3] Haojie Chai Xianming Chen Yingchun Cai 1 and Jingyao Zhao (2018) Artificial Neural Network Modeling for Predicting Wood Moisture Content in High Frequency Vacuum Drying Process. Forests 2019, 10, 16; doi:10.3390/f10010016 www.mdpi.com/journal/forests.

[4] Hongwei Wu and Stavros Avramidis 2006. Prediction of Timber Kiln Drying Rates by Neural Networks Department of Wood Science, The University of British Columbia, Vancouver, British Columbia, Canada.

[5] Janssens, C. (2018). Introduction to Prediction Research: *Manual on prediction.* 1-36

[6] Ojo A.K. (2017). Projecting the Future Direction of Publication Patterns Using Text Mining. *International Journal of Scientific and Engineering Research.* Vol. 8. No. 7.: 2218-2226.

[7] Ojo A.K. and Adeyemo A.B. (2013). A Comparison of the Predictive Capabilities of Artificial Neural Networks and Regression Models for Knowledge Discovery. *Information Systems, Development Informatics and Business Management* Vol. 4. No. 2: 27-32.

[8] Shengjun Wen, Mingcong Deng, Akira Inoue 2012. Moisture Content Prediction of wood Drying process using SVM-based model. *International Journal of Innovative Computing Information and Control* Vol. 8 (6):4083-4093

[9] Xiao-dong Zhu, Jun Cao, Feng-hu Wang, Jian-ping Sun, and Yu Liu 2009. Wood Defect Identification Based on Artificial Neural Network. © Springer-Verlag Berlin Heidelberg. ISICA, CCIS 51, 207-214.

[10] Zanuncio, Carvalho, Da Silva, Carneiro and Colodette 2016. Artificial Neural Networks as a New Tool for Assessing and Monitoring Wood Moisture Content. *Revista Árvore, Viçosa-MG,* Vol. 40 (3): 543-549.

[11] Zhang, Sun, CAO (2006): Modelling of temperature-humidity for wood drying based on time-delay neural network. *Journal of Forestry Research,* 17(2): 141-144.