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Prediction of the Amount of Raw Material in an Algerian Cement Factory

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Abstract: Factories are currently confronted with multifaceted challenges created by rapid technological Many technologies have recently appeared and evolved, including Cyber-Physical Systems, the Internet of Things, Big Data, and Artificial Intelligence. Companies established various innovative and operational strategies, there is increasing competitiveness among them and increasing companies' value. A smart factory has emerged as a new industrialization concept that exploits these new technologies to improve the performance, quality, controllability, and transparency of manufacturing processes. Artificial intelligence and Deep Learning techniques are revolutionizing several industrial and research fields like computer vision, autonomous driving, predicting failures, etc. The idea of this work is the development of a predictive model to predict the amount of raw material in a workshop in a cement factory based on the Deep Learning technique Long Short-Term Memory (LSTM). The excellent experimental results achieved on the LSTM model showed the merits of this implementation in the production performance, ensuring predictive maintenance, and avoid wasting energy.

Keywords: Intelligent automation, Smart manufacturing, Prediction, Deep learning, LSTM

Introduction

Companies have a vital need to adapt universally if they are to remain competitive. The automation has not eliminated the malfunctions that can cause unnecessary stoppages during the execution of the process. These problems have forced companies to look for effective solutions, such as the use of new technologies like Artificial Intelligence and Machine learning. The lack of a guiding theoretical framework of Machine Learning technology in manufacturing, the amount of redundant data, and the complexity of processes present a knowledge gap. Consequently, many problems are facing the applications of data analytics and machine learning in the industry at first (Kusiak, 2018; Sharma et al., 2021; Van Heerden & Bas, 2021).

In this work, we focus on new trends in the manufacturing field, particularly the industry 4.0 and the smart factory, which will revolutionize manufacturing systems. Along with the industry 4.0 revolution, in several industries, machine learning has been effectively used in process optimization (Li et al., 2020), monitoring and control applications in production, and predictive maintenance (Wang et al., 2021). Also, on new technologies like artificial Intelligence. We chose the cement factory to be our field of application to create a program for predicting the quantity of raw material in a raw mill workshop and the cement workshop using the deep learning algorithms the Long Short-Term Memory (LSTM).

Methods

Artificial Intelligence (AI) in a sense is the simulation or replication of intelligence processes by computer systems that can think and act rationally in a way similar to humans. In other words, AI can be defined as a branch of computer science by which we create intelligent machines which can think like a human, act like humans, and be able to make decisions like a human (Jokanović & Jokanović, 2021). Because it is relevant to such a wide range of use cases, machine learning is generating a lot of interest. Classification is a supervised learning method in machine learning in which the computer program learns from the data input given to it and then utilizes this learning to categorize new observations. Choosing an algorithm is a key stage in the machine learning process, so ensure it genuinely matches the problem's use case (Mohana-Priya et al., 2021; Usuga Cadavid et al., 2020).

Deep learning is a specific method of machine learning that incorporates neural networks in successive layers to learn from data iteratively. A neural network consists of three or more layers: an input layer, one or many hidden layers, and an output layer. Data is ingested through the input layer. Then the data is modified in the hidden layer and the output layers based on the weights applied to these nodes. The typical neural network may consist of thousands or even millions of simple processing nodes that are densely interconnected. Deep learning has become a powerful tool widely used in many fields like medicine, social media, and as this work in industry, with the help of its algorithms and one of the most important deep learning algorithms is recurrent neural networks (RNN). An architecture of Recurrent neural networks (RNN) is displayed in Figure 1.

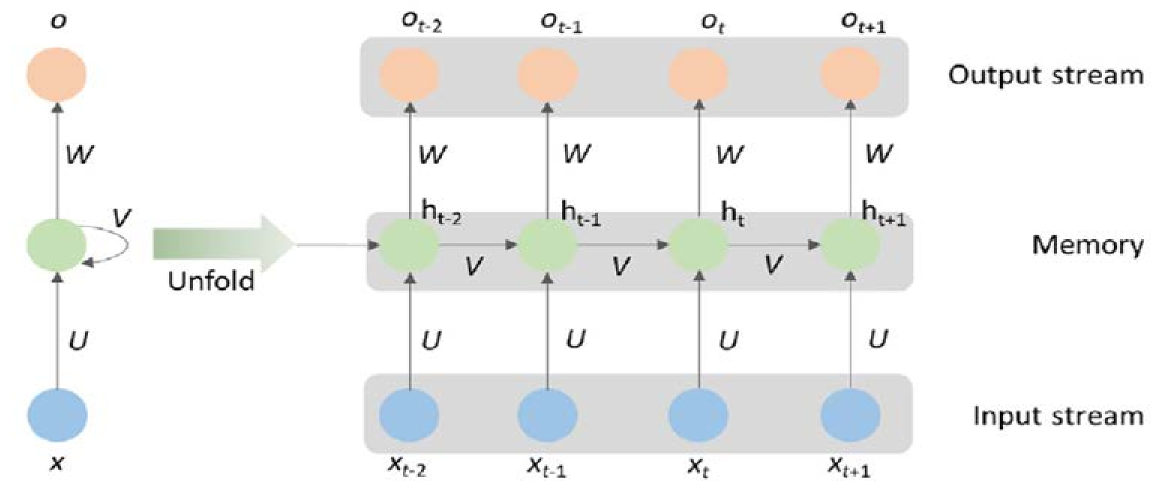

Figure 1. Architecture of RNN

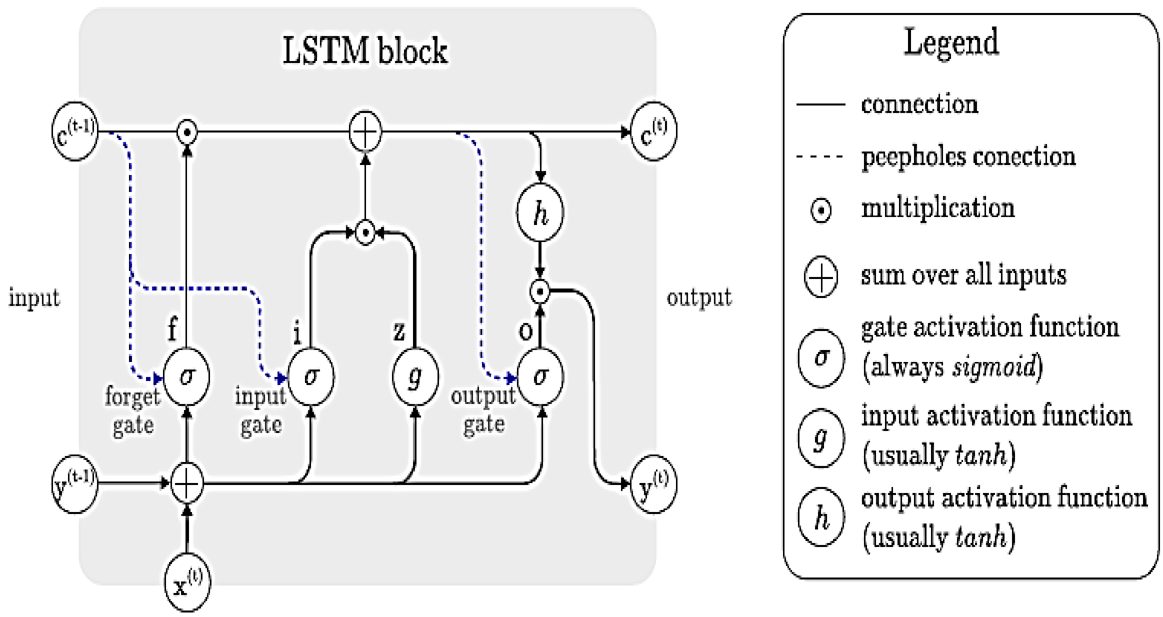

Figure 1. LSTM technique principle

The LSTM model is an extension for RNNs designed to overcome the exploding and vanishing gradient problems that typically arise when learning long-term dependencies, even when the minimal time lags are very long in between. this is because the LSTM model has three gats the input and the output gate, also the forget gate (Van Houdt et al., 2020).

Although RNNs are successful in short-term memory operations, they have failed to learn long-term dependencies. The most important reason for this is the vanishing and exploding gradient problem. Long Short-Term Memory (LSTM) is an extension of RNN has been introduced by Hochreiter and Schmidhuber in 1997 to solve the problem of vanishing gradient, one of the major difficulties in performing long-term memory. The architecture of the LSTM model is represented in Figure 2.

Materials

In this study, in an East Algerian cement plant of Ain Touta (SCIMAT), the workshop of a raw mill is selected. Throughout the production line, the product passes via a collection of electrical, mechanical, and automated equipment and a large number of other devices to process and maintain this operation and keep it on functionality mode if the system needs. Description of the workshop features are collected in Table 1.

Table 1. Description of the workshop features

Parameters	**Interval**	**Units**	**Designation**
Z2M03_J1	[0-120]	%	Engine Crusher Power
Z2M01_T3	[0-150]	C°	Crusher Temperature Output
Z2M01_T2	[0-150]	C°	Crusher Temperature Input
Z2M01_P2	[0-40]	mbar	Crusher Pressure Output
Z2M01_P1	[0-4]	mbar	Crusher Pressure Input
Z2M01_X1	[0-100]	%	Crusher acoustic equipment
Z2S01_S1	[0-100]	%	Separator Speed
Z2S01_I1	[0-120]	%	Separator Current
Z2J01_J1	[0-120]	%	Elevator Power
Z2S03_J1	[0-120]	%	Fan’s Power
Z2S05_Z01	[0-100]	%	Butterfly Register Position
Z2P06_Z01	[0-100]	%	Butterfly Register Position
Z2P25_Z1	[0-100]	%	Butterfly Register Position
Z2M03_T8	[0-150]	C°	Crusher Bearing Temperature
Z2M03_T9	[0-150]	C°	Crusher Bearing Temperature
Z2A01_F1	[0-140]	t/h	Transp.Tape Flow
Z2B01_F1	[0-140]	t/h	Transp.Tape Flow
Z2C01_F1	[0-8]	t/h	Transp.Tape Flow
Z2D01_F1	[0-40]	t/h	Transp.Tape Flow
Z2M01I01_TOTAL	[0-150]	t/h	Total Feed Rate
Z2M01_Y1_SPM	[0-140]	t/h	Total Feed
Z1L01_L21	[0-100]	%	Clinker Hopper Level
Z1L02_L21	[0-100]	%	Clinker Hopper Level
Z1L03_L21	[80-100]	%	Silo Cement Level
Z1L04_L21	[0-100]	%	Silo Cement Level
P1L03_L21	[0-100]	%	Silo Cement Level
P1L02_L21	[0-100]	%	Silo Cement Level
P1L01_L21	[0-100]	%	Silo Cement Level
P2L01_L21	[0-100]	%	Silo Cement Level
P2L02_L21	[0-100]	%	Silo Cement Level

Results and Discussion

The heatmap presented in Figure 3 illustrated the correlations between the different attributes of the selected dataset. All characteristics/features given in the dataset are very less correlated with each other. This implies that we have to include all the characteristics because we can only eliminate the characteristics where the correlation of two or more characteristics is very high.

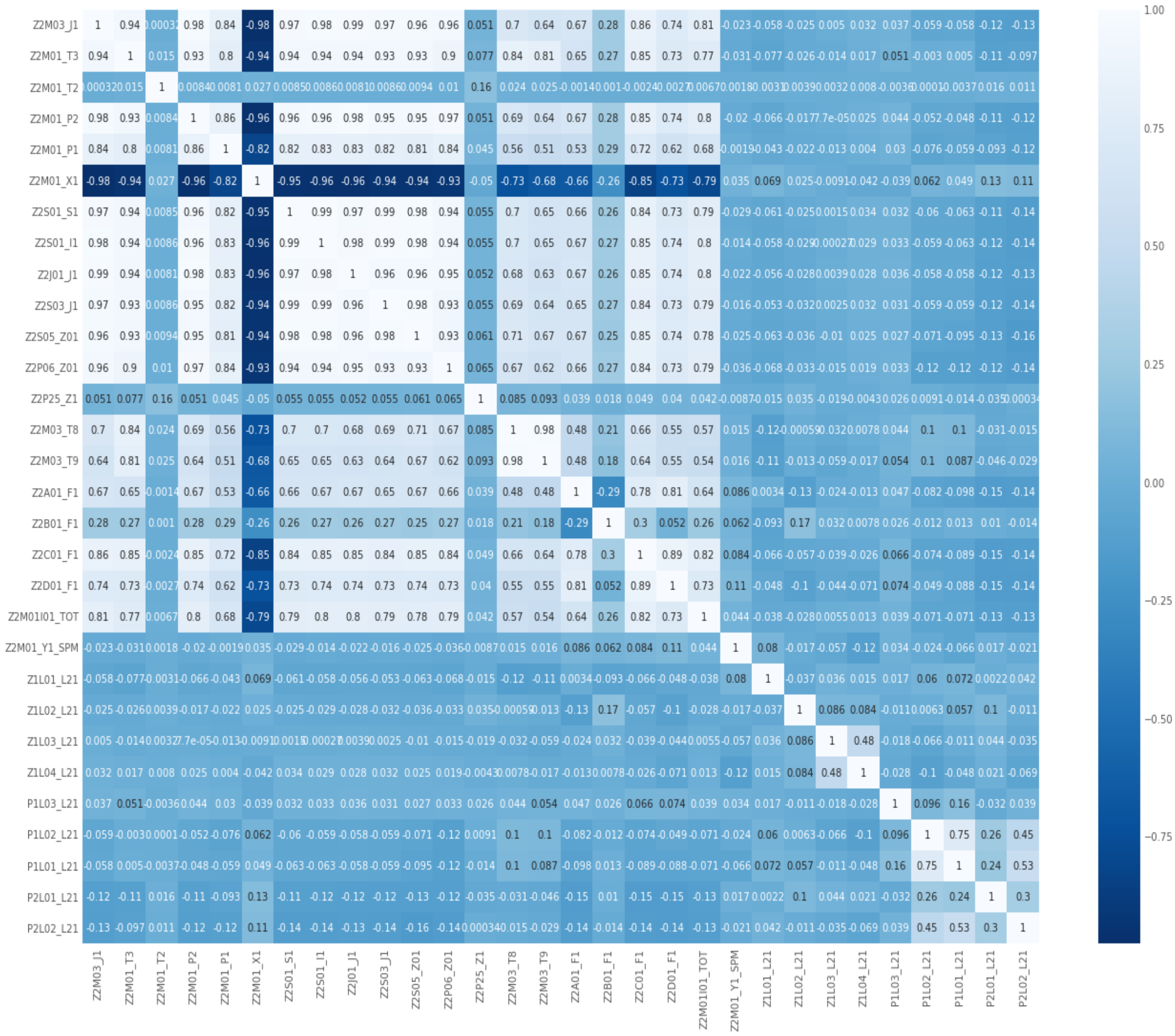

Figure 3. The heatmap of features.

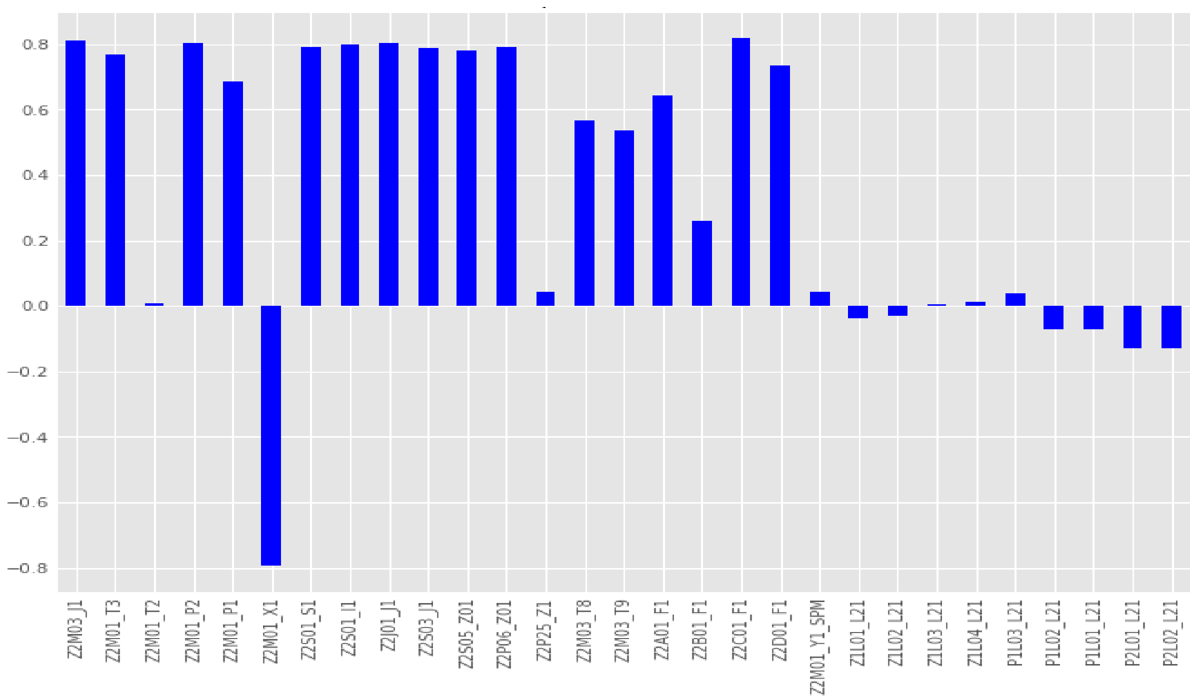

Figure 4. Influential factors

Regarding the plot displayed in Figure 4, several observations are noted. Factors indicators that influence negatively the state of the line production are the crusher acoustic indicator (M01X1) and the operator sp03 (QCXH20). Figure 3 displayed the different influential factors on the functioning of the line production. In our experiments, the data set is split into two parts, respectively as the training set (67%) and testing set (33%). The training set is used to train the prediction model while the testing set is used to validate the performance of the trained model.

More specifically, the accuracy of predictions on the testing set, the core and key of further applications, plays an essential part in the validation and directly affects whether it could be used. During the first stage, the LSTM algorithm is applied to a training dataset and the performance was evaluated. Later, the algorithms were applied to a testing dataset to make predictions (see Figure 5).

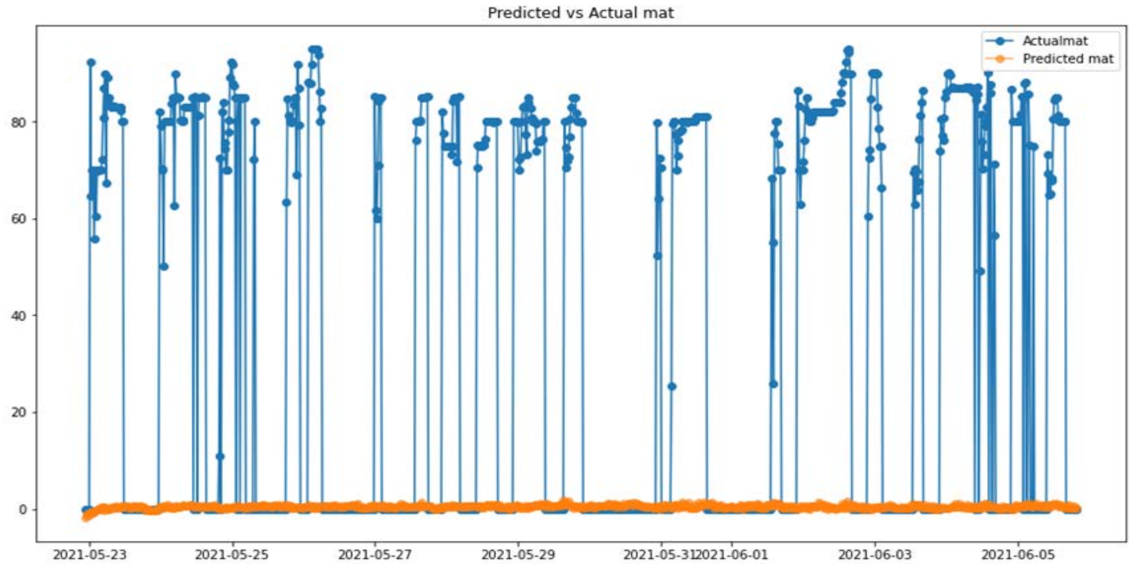

Figure 5. The prediction of first material with the LSTM algorithm.

Results demonstrate the overall system performance enhancement in predicting bearing failure when modeled data are included with SCADA data. Based on data from the cement plant, the performances of different machine-learning models on unseen data are then evaluated using industry-standard metrics including training accuracy, testing accuracy, sensitivity, and specificity. Evaluation results are collected in Table 2.

Table 2. The evaluation metrics of the predictive model

Metrics	Value
Mean Error (ME)	-21.16
Mean Absolute Error (MAE)	22.17
Root Mean Squared Error (RMSE)	40.94
Validation Loss	0.29

Conclusion

The learning model and architecture presented improve control flexibility. The capacity to handle data and a great deal of information to boost productivity, minimize maintenance costs, and several other advantages. In the future, we can use test the presented dataset with other improved machine learning algorithms to provide better efficiency.

Recommendations

We believe that the following research directions are required for the next generation of prognostic and health management systems, especially in complicated industrial processes with enormous real-time alarms and faults. The final objective is to obtain an autonomous system able to supervise the factory in real-time.

Scientific Ethics Declaration

The authors declare that they are responsible for the scientific, ethical, and legal aspects of the paper published in EPSTEM.

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