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Consistent Product Moisture Prediction in Manufacturing using Time Series Analysis

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Abstract— Maintaining a consistent moisture environment for a product is one of the key objectives in a manufacturing process. Mostly the product moisture is maintained by a temperature sensor which is manually controlled by a human who knows knowledge about the system and also supervising the temperature by human does not assure complete moisture control of the system. To address this problem, a time series model trained with a custom product moisture dataset which can predict the temperature to be maintained with 97% accuracy in the storage system has been implemented in the temperature system. In this time series model, Longest Short Memory Network is used as neural network architecture with some defined hyper parameters to achieve target accuracy.

Keywords—Time Series Model, LSTM, Moisture Control

I. Introduction

Quality is the collection of feature and characteristics of a product that contribute to its ability to meet requirements and also creating standards for producing acceptable products. During product manufacturing all the raw materials are gathered and stored in a effective environment to maintain the quality till it moves to process and production. For suitable environment for the product preservation a temperature control sensor is deployed in the storage unit which is supervised by an employee. Moisture content affects the physical, chemical, and microbiological properties of the products. To maintain standard moisture which is suitable for all the products temperature and humidity must be maintained in a specific limit.

Rest of the paper is organized as follows, Section I contains the introduction of the proposed work , Section II contain the related work of moisture prediction , Section III contain the proposed methodologies Section IV describes results and discussion and Section V concludes the proposed research work with future directions.

II. Related Work

This section, address some related works to time series methodology and artificial neural networks. In Artificial Neural Network Modeling for Temperature and Moisture Content Prediction in Tobacco Slices Undergoing Microwave-Vacuum Drying is shown in Fig 1. They used Artificial Neural Network (ANN) for maintaining moisture of the product in drying process they used ANN to predict and maintain a stable temperature in the storage system. The result of their experiments indicate that ANN models were able to recognize relationships between process parameters and product conditions. The model may provide information regarding microwave power and vacuum pressure to prevent thermal damage and improve drying efficiencies.[1]

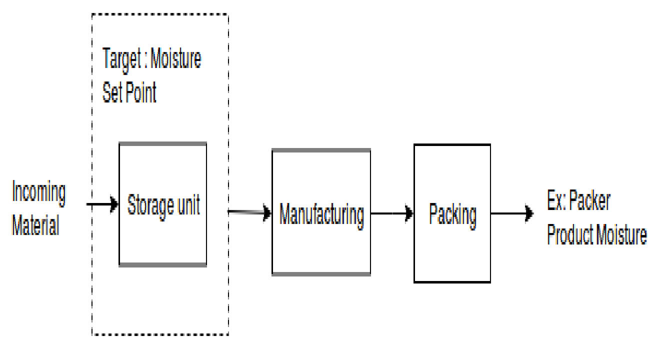

Fig 1. Tobacco Product Production Pipeline

Temperature and Relative Humidity Estimation and Prediction in the Tobacco Drying Process Using Artificial Neural Networks presents a system based on an ANN for estimating and predicting environmental variables related to tobacco drying processes. This system has been validated with temperature and relative humidity data obtained from a real tobacco dryer with a Wireless Sensor Network (WSN). A fitting ANN in the validation trails is shown in Fig 2. It is used to estimate temperature and relative humidity in different locations inside the tobacco dryer and to predict them with different time horizons. These results show that the tobacco drying process can be improved taking into account the predicted future value of the monitored variables and the estimated actual value of other variables using a fitting ANN as proposed [2].

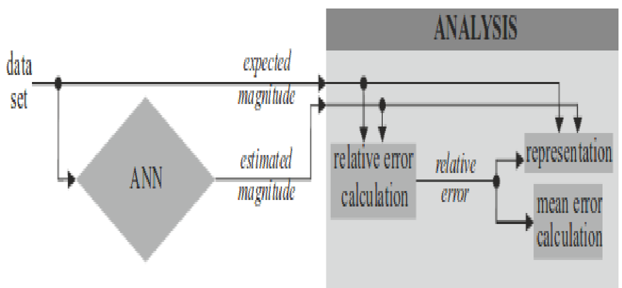

Fig 2 Validation trails of ANN system

Applying LSTM to Time Series Predictable Through Time-Window Approaches says that Long Short-Term Memory (LSTM) is able to solve many time series tasks unsolvable by feed-forward networks using fixed size time windows.The results suggest to use LSTM only on tasks where traditional time window based approaches must fail. One reasonable hybrid approach to prediction of unknown time series may be this: start by training a time window-based MLP, then freeze its weights and use LSTM only to reduce the residual error if there is any, employing LSTM's ability to cope with long time lags between significant events. LSTM's ability to track slow oscillations in the chaotic signal may be applicable to cognitive domains such as rhythm detection in speech and music [3].

III. Methodology

Custom LSTM network is proposed which is specially adapted for time series analysis . It's a sequential prediction problem so that LSTM network is preferred based upon the dataset and sequence flow of records .

A . Time Series Analysis :
From the underlying data , all the independent fields are dependent on the time and the prediction of temperature sensor predicted according to that . This problem is treated as Multivariate Time Series analysis problem due to its multiple features and sequence . To obtain accurate prediction, it is crucial to model long-term dependency in time series data, which can be achieved to some good extent by Recurrent Neural Network with attention mechanism. Typical attention mechanism reviews the information at each previous time step and selects the relevant information to help generate the outputs, but it fails to capture the temporal patterns across multiple time steps.[4]

B . Long Short Term Memory :
Long Short-Term Memory (LSTM) neural networks as an approach to build consistently accurate models for a wide range of predictive process monitoring tasks. [5]

While potentially containing a wealth of insights, the data is difficult to mine effectively, owing to varying length, irregular sampling and missing data. RNNs, particularly those using LSTM hidden units, are powerful and increasingly popular models for learning from sequence data. They effectively model varying length sequences and capture long range dependencies. This study is to empirically evaluate the ability of LSTMs to recognize patterns in multivariate time series of required measurements.[6]

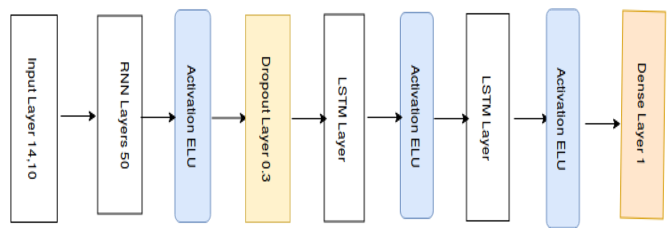

Fig 3 . Proposed Neural Network Architecture

The sequence of the data which is separated by the date . For each date there is at least 3 - 10 sequence of data points . From the visualization identified that the deviation of temperature in label is in short deviation in dates .

Deep Learning is referred due to large availability of data and ease the LSTM implementation . Model training system follows all the general procedures of data mining and finally during modelling a customized version of LSTM network is implemented after trial and error steps .

For deep learning model there is no need for lots of preprocessing and feature engineering ,so cleaning and making a structured flow of dataset . Advantage of LSTM network is that model can be trained by the previous sequence of outputs . Before fitting the data to the model , sort the data based upon the timing records to avoid sequence collapse .

Model in the system is implemented using Tensorflow and using their core modules . The finalized architecture for time series model is represented in Fig 3 .In this architecture Fig 3, the input layer has 14 feature inputs for a data point and 10 sequence of inputs . Initial training layer is fed into RNN layer of 50 with the activation layer of Exponential Linear Unit (ELU) and then to avoid overfitting it is fed into dropout layer of ratio of 0.3 . LSTM layer follows the rest of the training job with the given sequence and same activation method is used for the next two layers . Finally regress to a single value of the feature map from the final LSTM layer . The loss of the prediction is analyzed using Mean Average Error (to reduce by the absolute difference of the actual and predicted results. To reduce the loss values in the feature network Adam optimizer with the learning rate of 0.001 is used .

Training the data with the mentioned configuration for 20 epochs in a Nvidia GTX machine for 1 hr approximately gives the prediction model . After the final evaluation in the validation set the model is deployed in a micro service application enabled with IOT connection in the temperature sensor .Then timely the system sets the temperature to maintain the moisture content of the product .

IV. RESULTS AND DISCUSSION

The proposed technique has been extensively evaluated in real time datasets with regular conditions, shapes and lengths. It has also been compared with state-of-the-art techniques and analyzed via ablation analysis to be described in the ensuing subsections.

A . Datasets

The dataset which the prediction system is developed in real time data collected and published by a private organization for research purpose . The dataset contains 13 feature variables and 4442 data points . The features are raw materials used , product categories , number of days stored, date of manufacture , temperature , humidity in ambience and storage area . The target variable is product moisture.

B . Implementation

The proposed technique is implemented using Tensorflow on a regular GPU workstation with 2 Nvidia Geforce GTX 1080 Ti, an Intel(R) Core(TM) i7-7700K CPU @4.20GHz and 16GB RAM. The network is optimized by Adam optimizer with a starting learning rate of 10−4.

C . Experimental Result

In the final results , Mapping of future prediction of the temperature for the final last 20% sequence of validation set is done as shown in Fig 6. Also visualization for the complete dataset according to time series methodology as shown in Fig 5. Then the most independent feature is identified using the correlation graph in Fig 4. After cleaning and feature engineering the dataset , the model is fitted to the model and the sequence of results is produced comparing to validation results .

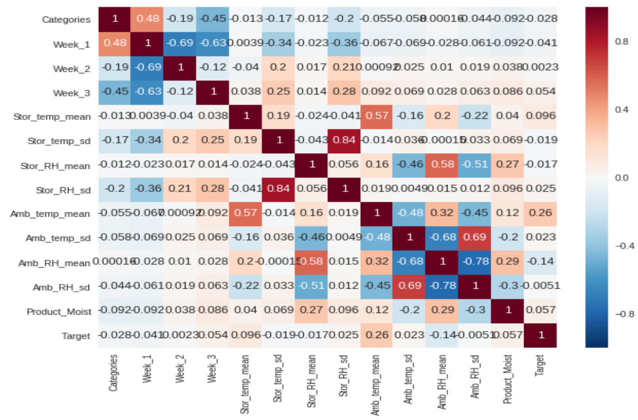

Fig 4 . Correlation Mapping of Feature

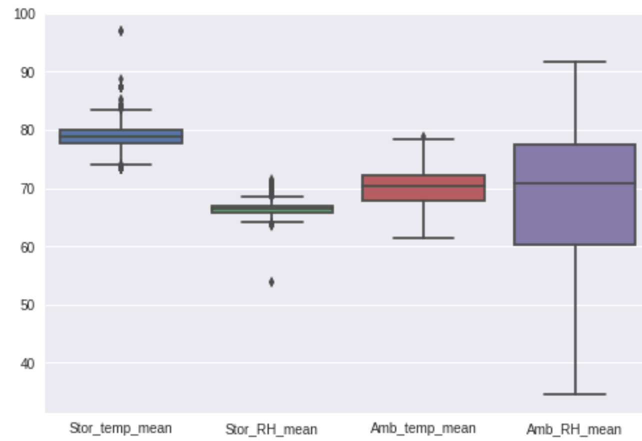

Fig 5 . Distribution of values and outliers detection

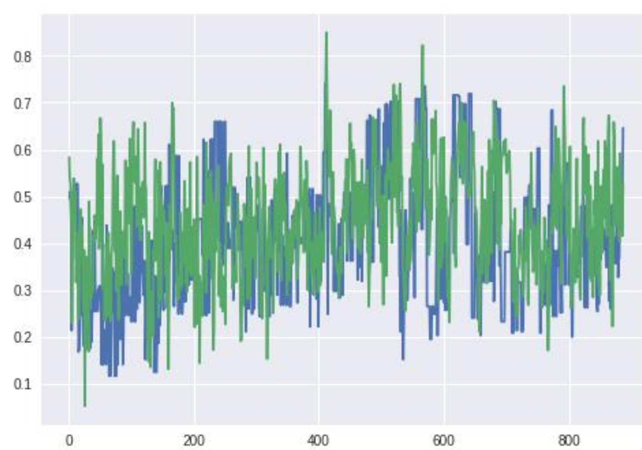

Fig 6 . Actual vs Predicted mapping in validation graph

V. CONCLUSION AND FUTURE SCOPE

This paper presents new scheme of applying neural network concept for moisture prediction using time series analysis methodologies. This implementation can be used in any IOT devices in storage system for real time prediction deployed with the model. Also continuous model updates and system upgradation can be done easily. This improves the product moisture as per the deliverables for the industry.

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