The European Journal of Research and Development

journals.orclever.com/ejrnd

OR CLEVER Science & Research Group

Research Article

Sale Prediction in Textile Industry with Hybrid Deep Learning Using Time Series Images

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(First received March 06, 2022 and in final form June 06, 2022)

Abstract

In 2021, exports of 12.9 billion dollars in the field of textiles in Turkey's exports have an important place in all export income. In the reports published on the textile industry, this figure is expected to increase even more in the coming years. As in other sectors, accurate estimation of sales revenues in the textile sector is very important for the future plans of companies. In this study, a deep learning model has been developed for demand and sales forecasting in the textile industry. In the method used, income will be converted to image data with Gramm Angular Fields of time series. Convolutional neural networks were used to classify these images.

Keywords: Time Series, Gramian Angular Field, Deep Learning

1. Introduction

Textile companies need to improve their supply chain management in order to reduce their stocks and achieve the targets they set. For this, they need sales forecasting systems adapted to the uncertain environment of the textile field. Noisy data that influences uncertainty selling behavior is characterized by short historical data and a large number of explanatory variables. Textile managers need efficient and accurate forecasting systems to set up all the logistics steps needed to manufacture and distribute a product. An appropriate sales forecast, which allows to predict sufficient production quantity in a timely manner, is one of the most important factors for the success of the correct production program (Giering, 2008). Forecasting is an important planning tool for the decision-making process (Kohli et. al., 2021; Ribeiro et. al., 2017; Vengatesen et. al., 2020). The success of Supply Chain Management optimization depends on the quality of finished product sales and the forecast of potential sales for the next period (Seyedan and Mafakheri, 2020).

Sales prediction accuracy depends on the correct interpretation of as much information as possible. To summarize, such a textile sales forecasting system requires:

- rapid response to a significant trend and seasonality change
- identify and fix completely random events
- forecast on short historical sales data
- taking into account the effects of explanatory variables.

There are different estimation models such as explanatory or extrapolative linear/non-linear adaptive or non-exponential smoothing models (eg Holt-Winters), Box-Jenkins model and autoregressive integrated moving average (ARIMA) processes, dynamic explanatory variable regression models, econometric methods (Weigend, 2018) and more recently artificial neural networks (ANN) or fuzzy logic based models (Frank et. al., 2001; Kasabov and Song,2022; Thissen et. al., 2003). The major disadvantage of the mentioned methods is that almost all implementations are quite specific and often have to use a combination of several prediction models. One success, especially available in the textile-clothing industry network, is trying to get an estimate. The inability to control and fully define the events that may affect the forecasting system are the biggest difficulties in producing forecasts for the textile industry (Duarte et. al., 2018). Also, the number of important parameters in some models makes short historical learning difficult. In cases where the serial number is important, automatic methods are preferred. In addition, a manual model setting may be more precision with a strong explanatory variable effect. The structure and learning procedure of the models are adapted to the short and noisy time series as well as the mean-term forecast horizon.

A feature of textile sales analysis is that it includes a wide range of products and a significant number of product references. For this, first of all, data such as clustering must be preprocessed (Trivedi et. al., 2015). The challenge in this analysis is to determine the level of aggregation of sales forecasts. These levels are determined according to the usage profile and production characteristics of the textile product. The choice to be made should allow the influence of explanatory variables to be addressed. In fact, the higher the aggregation level, the greater the interdependence between endogenous and exogenous variables, making modeling sales extremely difficult.

In recent years, deep learning methods and techniques have been successfully applied to challenging prediction periods of various real-world problems, including time series prediction (Han et., al, 2019; Yan and Ouyang, 2018). Despite the noisy and chaotic nature of the time series estimation problem, these techniques constitute the appropriate methodology and are quite successful in obtaining more accurate estimation. Long short-term memory (LSTM) networks and convolutional neural networks (CNNs) are probably the most popular, efficient and widely used deep learning techniques (LeCun et. al, 2015;

Shrestha and Mahmood, 2019). LSTM models can efficiently capture sequence pattern information thanks to their special architectural design, while CNN models can identify more valuable features by filtering out the noise of the input data. Because of these features, it is more suitable for the final forecasting model of LSTM and CNN time series. However, while standard CNNs are quite useful for processing spatial autocorrelation data, they are often not adapted to properly manage complex and long temporal dependencies [4]. While LSTM networks are suitable for dealing with temporal correlations, they only take advantage of the features provided in the training set. Since both models have advantages and disadvantages, both deep learning techniques should be used together to improve the prediction performance of the time series model. The main purpose of this study is to contribute to an accurate forward-looking sales forecast in the textile industry by obtaining images from the time series by converting the textile sales time series to Gramian Angular Fields (GAF) and classifying them with LSTM-CNN network. More specifically, the proposed model predicts forward sales by leveraging the capacity of the convolutional layers to gain useful insights and learn the internal representation of time series data, as well as the effectiveness of the LSTM layers for short-term and short-term identification. More specifically, the model predicts next year's sales by analyzing sales data from past years.

2. Materials and Methods

Gramian Angular Field (GAF) imaging, which is suggested by Wand and Oates (2015), is an elegant and efficient way to encode time series as images. In order to obtain GAF images, we first need to rescale of the real observations. Let X= 〖{x_i }^N〗_(i=1)be a time series. Then, by using mean normalization

$$\hat{x}_i = \frac{2x_i - \max X - \min X}{\max X - \min X} \tag{1}$$

we obtain rescaled time series $\hat{X} = \{\hat{x}_i\}^N{}_{i=1}$whose elements are in $[-1,1]$. Moreover, by computing the angular cosine of every element by using

$$\theta_i = \arccos(\hat{x}_i)\,, \hat{x}_i \in \hat{X}, \quad r_i = \frac{i}{N},\ i \leq N, \tag{2}$$

$\hat{X}$ can be transformed to polar coordinates. Finally, Gramian summation angular field (GASF) and Gramian difference angular field (GDAF) can be obtained by

$$GASF = \cos(\theta_i + \theta_j) \tag{3}$$

$$GADF = \sin(\theta_i + \theta_j) \tag{4}$$

The GASF and GADF images obtained as a result of the mean normalization of the time series in meters of the annual fabric sales made by YÜNSA between 2011 and 2020 are given in Figure 1.

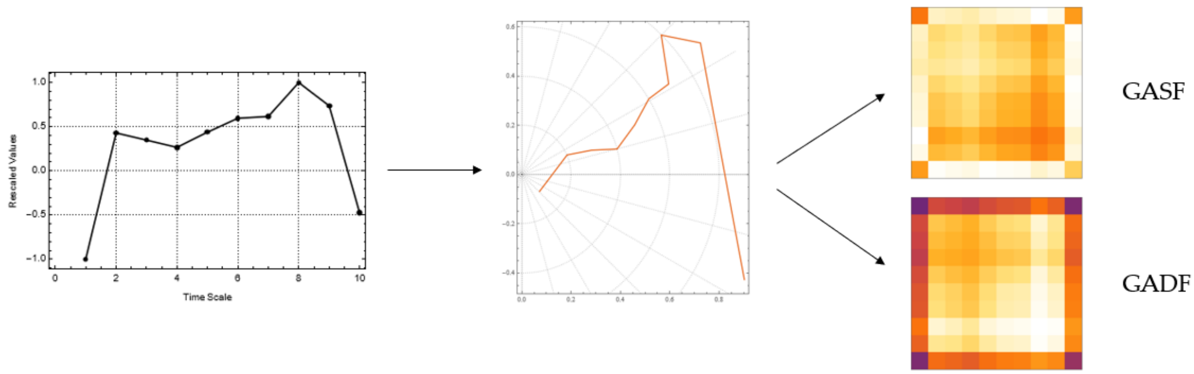

Figure 1 GASF and GADF images

In this article, using advanced deep learning techniques, a forecasting model is proposed to obtain meaningful results from sales figures of past years and to accurately forecast sales through GASF and GADF images. While short-term and long-term dependencies are determined by LSTM networks, convolutional layers are used to reveal useful information and characterize the internal representation of time series data with learning capabilities. The main idea of our proposed model is to efficiently combine the advantages of these deep learning techniques.

For this purpose, the proposed model consists of two main components called CNN-LSTM: The first component consists of convolution and pooling layers, in which complex mathematical operations are performed to improve the properties of the input data. The second component consists of features created by LSTM and dense layers.

The convolutional and pooling layers are data preprocessing layers for filtering the input data and extracting useful information. Then, usually extracted information is used as input in a fully connected network layer. Convolution layers perform convolution between raw input data and convolution kernels that generate new feature values. The input data should be in a structured matrix form because this method is designed to extract image features. The convolution filter can be thought of as a small sized window containing the coefficient values by encoding them in a matrix. This window is shifted across the whole matrix by applying a convolution operation to each subregion. Finally, a matrix is obtained representing a property value specified by the coefficient values and the size of the applied filter. By applying different convolution kernels to the input data, multiple convolutional features can be generated. This generation is useful than the initial features of the input matrix and improves the performance. Convolutional layers are usually followed by a non-linear activation function followed by a pool layer. Pooling layer is a subsampling technique that extracts certain values from convolutional features and produces a lower dimensional matrix. The pooling layer uses small sized sliding window similar to the convolution lair. However, this window takes the values of each convolution feature patch as input. Then, produce new determined values as outputs. Maximum pooling and average pooling calculate the maximum and average value of the values of each patch. As a result, the pooling layer generates new matrices that can be considered as summarized versions of the convolutional features produced by the convolutional layer. Pooling is important for the robustness of the system.

LSTM neural networks are a special type of recurrent neural networks (RNN) that can learn long-term dependencies. LSTM tries to solve the problem of feedforward neural networks called memory gap. In order to acquire short-term memory and capture information, LSTM uses cyclic connections in hidden layers. Performances of RNNs are not efficient to solve long range dependencies because of the vanishing gradient problem. However, LSTM comes over this problem by storing useful information and removing redundant information. Hence, LSTM results better performance than a classical RNN.

Each LSTM unit consists of a memory cell and three main gates: in, out and forget. With this structure, LSTM manages to create a controlled flow of information by deciding which information should be forgotten and which information should be remembered. Therefore, long-term dependencies can be learned. More specifically, input port i_t, together with a second port c_t^*, checks for new information stored in memory state c_t at time t. The forget gate f_t controls the historical information that must be lost or stored in the memory cell at time $t-1$, while the output gate o_t controls what information can be used for the output of the memory cell. Then, the following equations briefly describe LSTM unit operations:

$$f_t = \sigma\left(U_g\, x_t + W_g\, h_{t-1} + b_g\right) \quad (6)$$

$$c_t^* = \tanh(U_c\, x_t + W_c\, h_{t-1} + b_c) \quad (7)$$

$$c_t = g_t \odot c_{t-1} + i_t \odot c_t^* \quad (8)$$

$$o_t = \sigma(U_o\, x_t + W_0\, h_{t-1} + b_o), \quad (9)$$

where x_t represents the input, the W^* and U^* are weight matrices, b_* are the vectors of the bias term, σ is the sigmoid function, and $\odot$ operator component-wise multiplication. Finally, the latent state h_t that generates the output of the memory cell is calculated as:

$$h_t = o_t \odot \tanh(c_t), \tag{10}$$

In case several LSTM layers are stacked together, both the memory state c_t and the hidden state h_t are passed as input to the next LSTM layer.

The CNN-LSTM model we use in this study is presented in Figure 2.

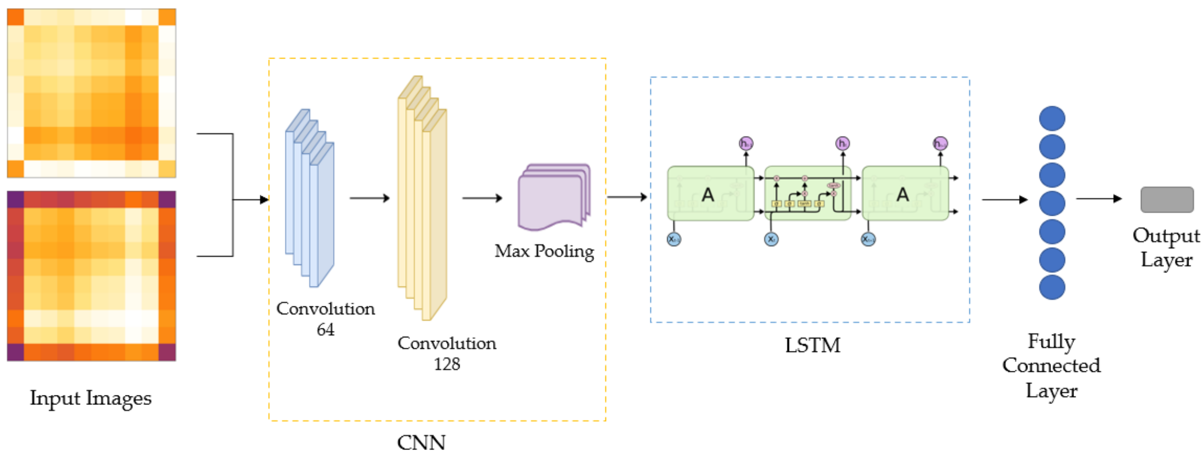

Figure 2 CNN-LSTM Architecture

3. Results

In this study, the values in meters of fabric sales made by YÜNSA from the beginning of 2018 to the middle of 2021 and the time series of the incomes from the sales are used. YÜNSA, the largest fabric manufacturer in Europe and the fifth largest in the world, has different fabric types in its portfolio. There are 222 time points in both of the time series obtained in this study. Since each fabric type will have different pricing, these time series have different values. However, it can be seen from the normalized time series given in Figure 3 that there is also a correlation between the number of meters and income. It is also possible to talk about the seasonality of time series in the related figure.

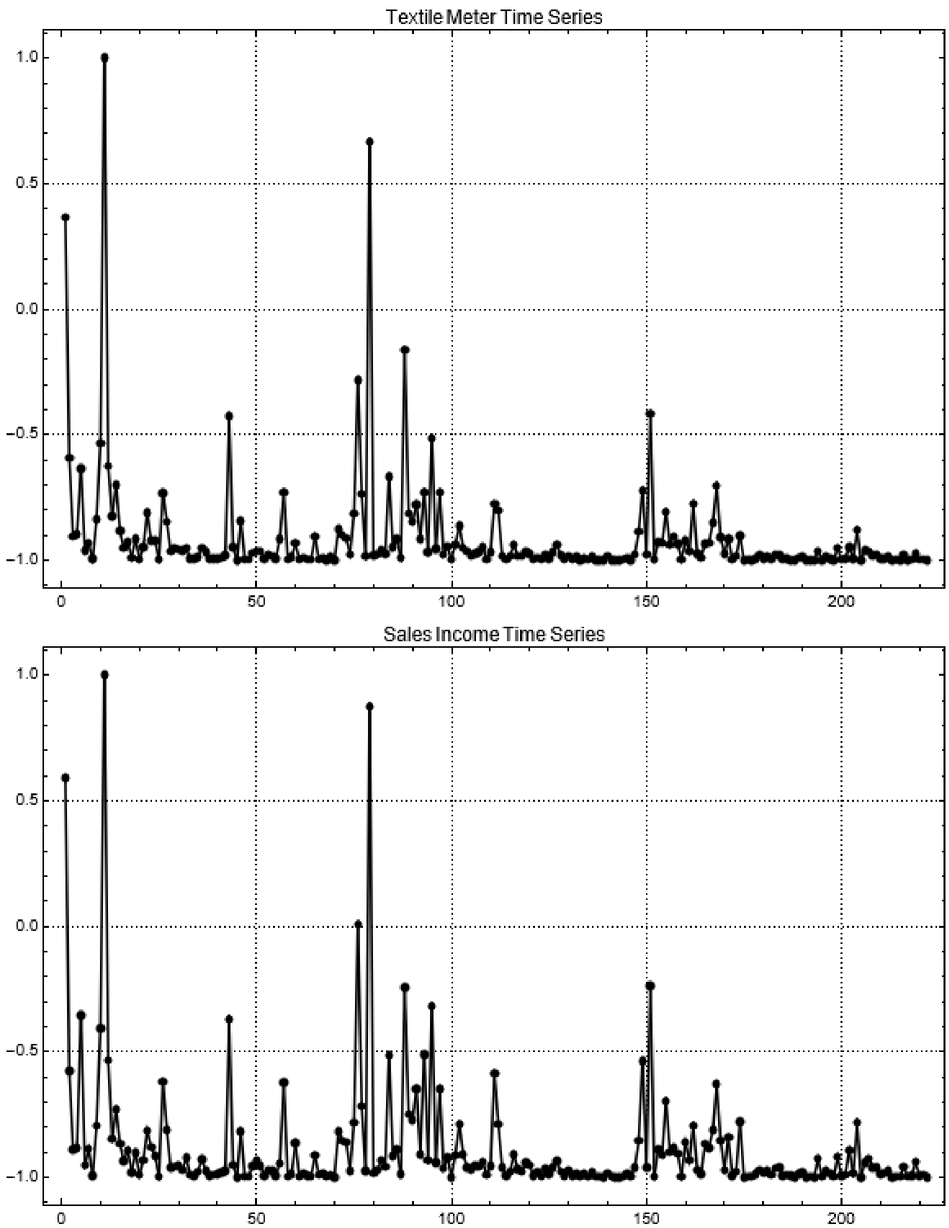

Figure 3 Mean Normalized Time Series

In order to obtain GASF and GADF images from the time series of the number of meters and income, the time windows of the time series with 28 steps and 1 offset are used. Thus, 195 GASF and 195 GADF time series images of 28×28 type corresponding to their sliding windows are obtained for each time series. Two types of comparisons were made in order to see the effectiveness of the hybrid method used in this study. The first of the comparisons is to make a price estimation by classifying the images of time series with a well-known deep network model LeNet. The second comparison model is made by running the Autoregressive integrated moving average (ARIMA) model on the sliding time series data.

Results for predictions are presented in Figures 4-6 for textile meter time series and in Figures 7-9 for sales income time series.

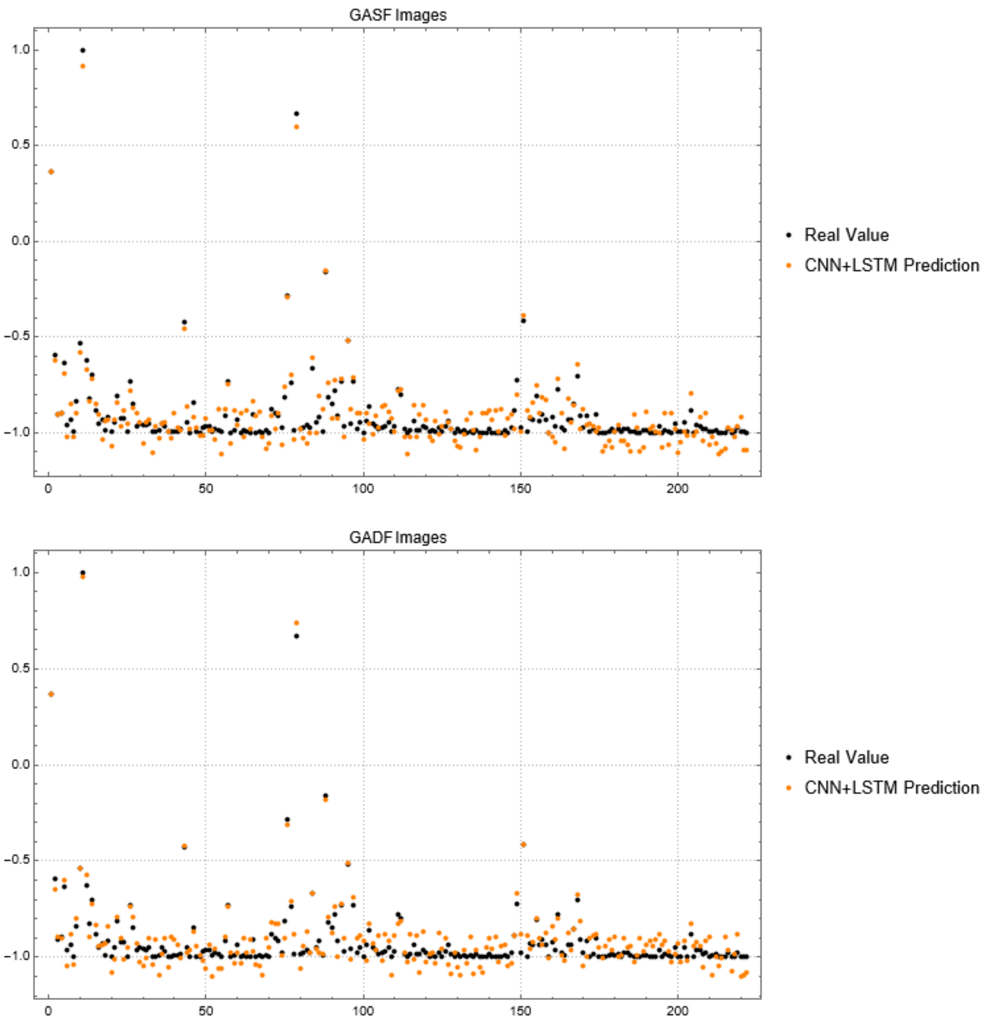

Figure 4 Sales meter prediction with CNN+LSTM method

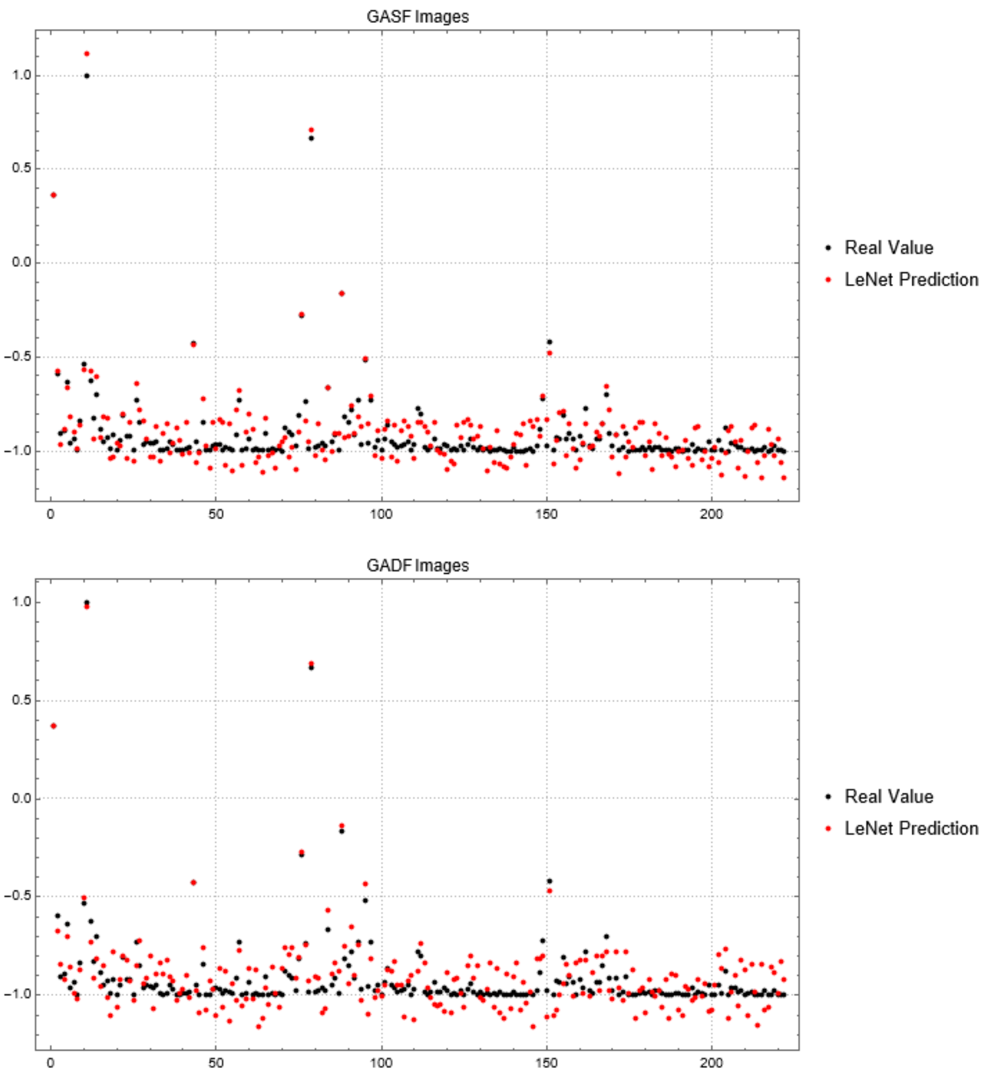

Figure 5 Sales meter prediction with LeNet method

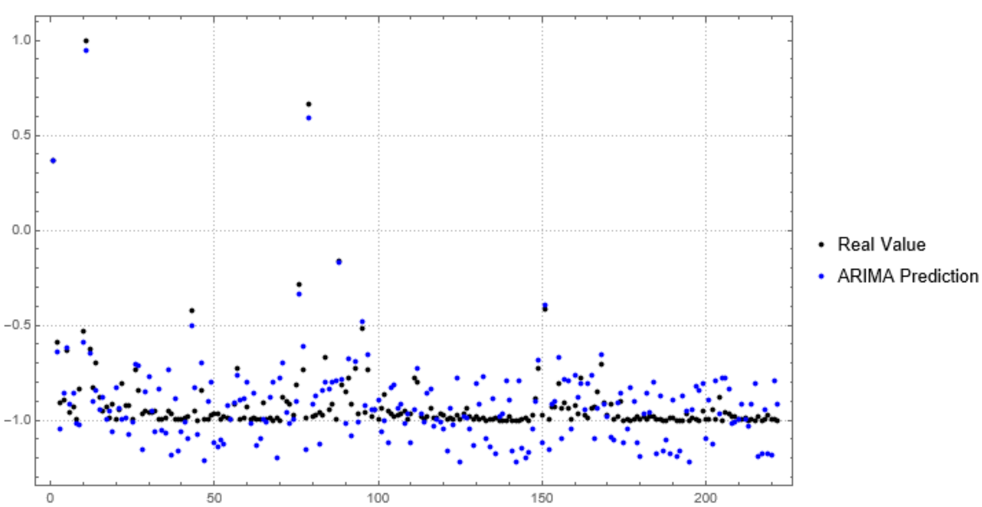

Figure 6 Sales meter prediction with ARIMA

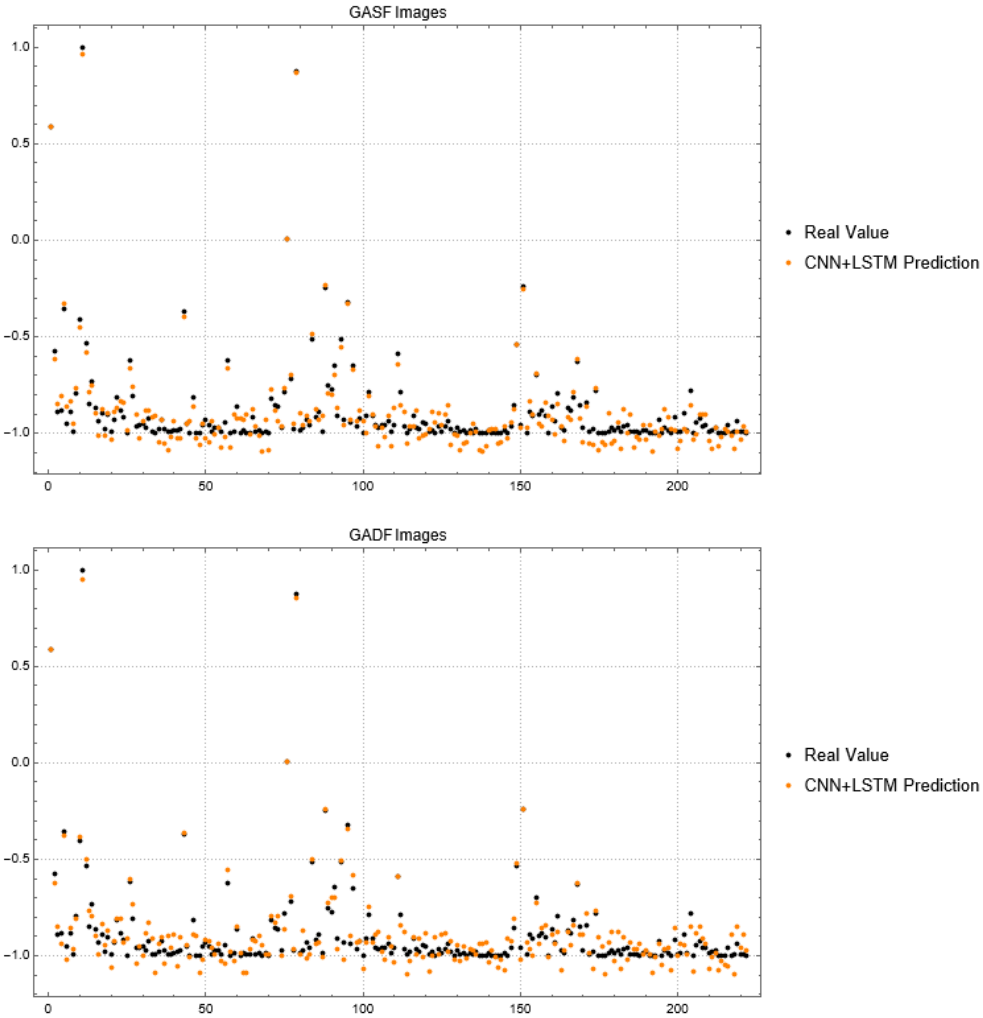

Figure 7 Sales income prediction with CNN+LSTM

https://doi.org/10.56038/ejrnd.v2i2.67

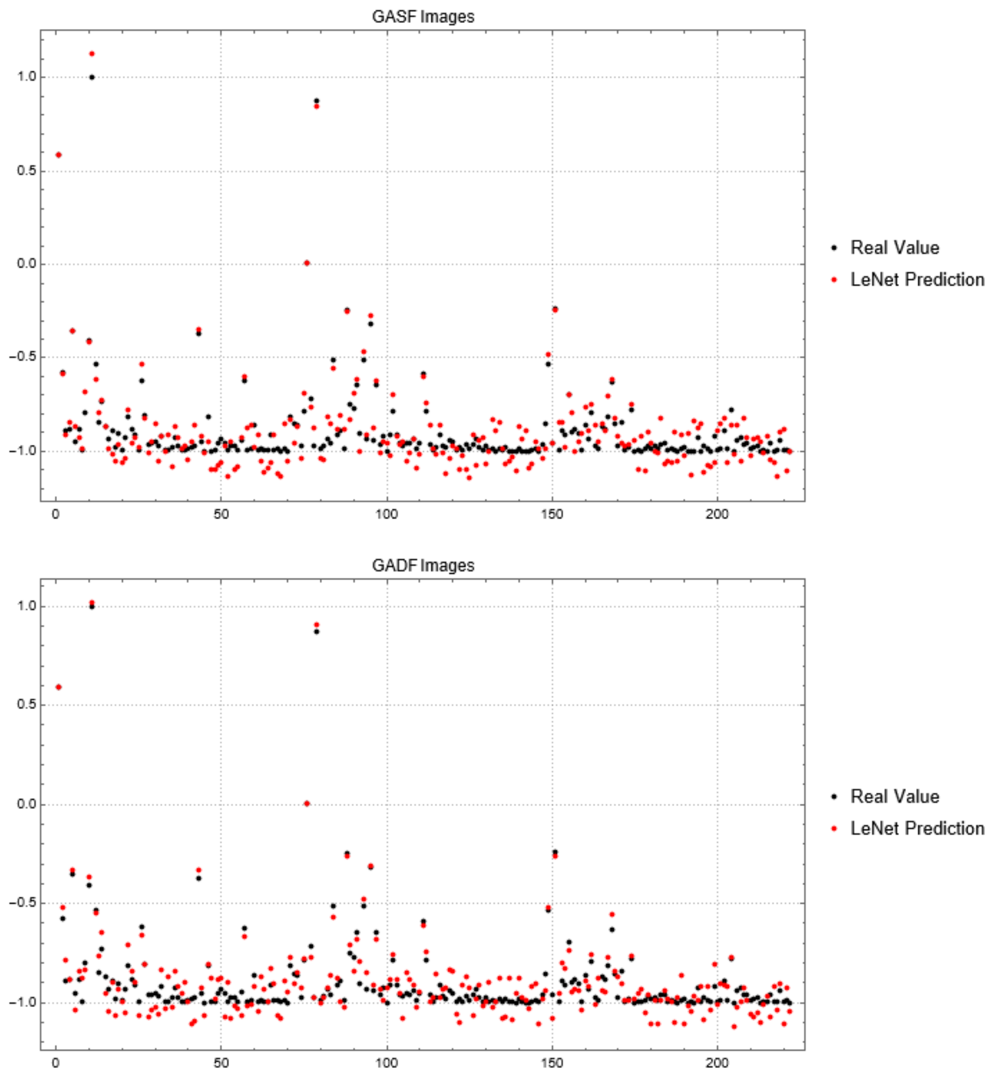

Figure 8 Sales income prediction with LeNet

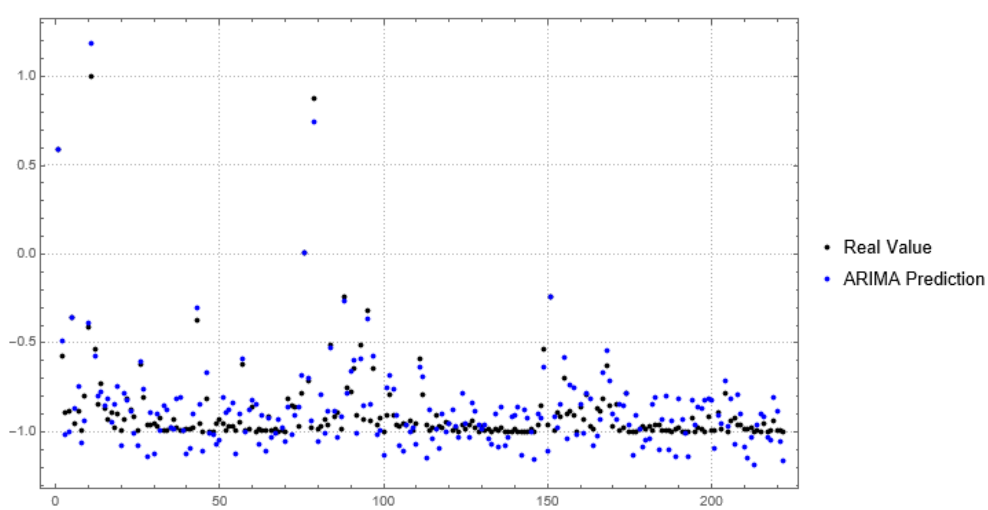

Figure 9 Sales income prediction with ARIMA

The hybrid method used in this study and the LeNet network are image classifiers. ARIMA works directly on time series data. For this reason, GASF and GADF images are examined separately in the comparison of hybrid networks and LeNet networks. In Table 1, the percentage values of the maximum, minimum and average prediction errors of these three methods are given.

Table 1 Percentage prediction errors

		Error (%)		
Method	**Image**	**Min**	**Max**	**Mean**
CNN+LSTM	**GASF**	0.013	15.28	12.16
	GADF	0.012	17.67	11.67
LeNet	**GASF**	0.012	20.64	15.46
	GADF	0.015	21.12	16.24
ARIMA		0.103	25.43	20.21

4. Discussion and Conclusion

Improvements to be made by textile companies in their supply chain management enable them to reach their targets. These improvements are achieved through the sales forecasting process. In this study, a method is presented that predicts the textile industry to sell fabric in meters and to generate sales revenue according to different fabric types. This method performs a prediction by classifying images obtained from time series of historical fabric sales data with a hybrid deep learning architecture.

In our study, firstly, past sales time series were examined for two cases as sales meter and sales return. It is seen that these time series show high positive correlation. In addition, the time series contains seasonality and can be observed to be noisy.

In order to obtain 28×28 type images, these time series are divided into sub-time series with a sliding window. The polar coordinates of each sub-time series are obtained by arccos transform. GASF and GADF images defined by angular correlation in polar coordinates appear as images belonging to these sub-time series. In our study, these time series images are classified with CNN+LSTM and LeNet networks and sales prediction is performed. When the sales forecasts are examined, it is seen that the method presented in this study generally contains less errors than the results obtained from the LeNet network. However, it has been observed that the LeNet network gives better results for

low volume sales, both in terms of meters and in terms of income. In addition, although less errors occur in the GASF method between GASF and GADF images, this differentiation is not very high.
ARIMA, one of the classical time series estimation methods, is also compared with the method presented in this study. The ARIMA method gives higher error rates compared to both the hybrid network presented in the study and the LeNet network. This shows the effectiveness of deep learning approaches in sales forecasting methods. Acknowledge

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