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Spectral temporal graph neural network for multivariate agricultural price forecasting

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ABSTRACT: Multivariate time series forecasting has an important role in many real-world domains. Especially, price prediction has always been on the focus of researchers. Yet, it is a challenging task that requires the capturing of intra-series and inter-series correlations. Most of the models in literature focus only on the correlation in temporal domain. In this paper, we have curated a new dataset from the official website of Turkish Ministry of Commerce. The dataset consists of daily prices and trade volume of vegetables and covers 1791 days between January 1, 2018 and November 26, 2022. A Spectral Temporal Graph Neural Network (StemGNN) is employed on the curated dataset and the results are given in comparison to Convolutional neural networks (CNN), Long short-term memory (LSTM) and Random Forest models. GNN architecture achieved a state-of-the-art result such as mean absolute error (MAE): 1,37 and root mean squared error (RMSE): 1.94). To our knowledge, this is one of the few studies that investigates GNN for time series analysis and the first study in architecture field.
Key words: Temporal GNN, time series, CNN, LSTM, forecasts.

Rede neural de gráfico temporal espectral para previsão de preços agrícolas multivariados

RESUMO: A previsão multivariada de séries temporais tem um papel importante em muitos domínios do mundo real. Especialmente, a previsão de preços sempre esteve no foco dos pesquisadores. No entanto, é uma tarefa desafiadora que requer a captura de correlações intra-séries e inter-séries. A maioria dos modelos na literatura foca apenas a correlação no domínio temporal. Neste artigo, selecionamos um novo conjunto de dados do site oficial do Ministério do Comércio Turco. O conjunto de dados consiste em preços diários e volume comercial de vegetais e abrange 1.791 dias entre 1º de janeiro de 2018 e 26 de novembro de 2022. Uma Rede Neural de Gráfico Temporal Espectral é empregada no conjunto de dados curado e os resultados são fornecidos em comparação com CNN, LSTM e Modelos de Floresta Aleatória. A arquitetura GNN alcançou um resultado de ponta (MAE: 1,37, RMSE: 1,94). Até onde sabemos, este é um dos poucos estudos que investiga GNN para análise de séries temporais e o primeiro estudo na área de arquitetura.
Palavras-chave: Temporal GNN, séries temporais, CNN, LSTM, previsões.

INTRODUCTION

Agricultural production is highly affected by natural conditions due to its general characteristics. As a natural consequence of this situation, farmers are faced with risks and uncertainties in the production process (GIRDŽIŪTĖ, 2012). In particular, adverse climatic conditions, diseases, pests and price uncertainties affect production negatively (DONG, 2021).

In Turkey, farmers are faced with significant price uncertainties due to the small scale of agricultural enterprises, insufficient production planning and the lack of effective marketing organizations. For this reason, farmers usually take into account the prices of the previous year when making production decisions (KIZILTIĞ & DAĞISTAN, 2021). This situation creates fluctuations in the amount of production and prices in agricultural product markets. As a result, product supply is the main factor that determines the market equilibrium of products (PIOT-LEPETIT & M'BAREK, 2011). This situation, which is called the Spider Web Theorem (Cobweb) in the economics literature, is frequently experienced in agricultural production (RAMADHANI et al., 2020). A certain time must pass between the decision and the production of products. In the face of changes in product demand during this time, farmers cannot immediately increase their product supply. As a result, large fluctuations arise between the amount of product and its prices (XIE & WANG, 2017).

As commodity prices affect global economic activity, accurate forecasting of commodity prices has become a very important issue for producers, intermediaries, exporting and importing

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countries (DUARTE et al., 2021). Commodities continue to be an important source of export revenue in most countries, particularly in developing countries, and commodity price movements have a major impact on overall macroeconomic performance (ZAFAR, 2007). Volatility and unexpected changes in agricultural commodity prices directly affect our daily lives. Fluctuations in agricultural commodity prices affect supply and demand; therefore, accurate estimation of prices helps to assess and protect the risks arising from price fluctuations (GU et al., 2022).

Time series analyzes are successfully applied in estimating the possible future value based on historical data. It is used in various fields such as traffic density estimating (BHATIA et al., 2020), air pollution predicting (WEN et al, 2019), supply chain management (ZHU et al., 2021) and financial investment (LIVIERIS et al., 2020). If the future development of events or metrics can be accurately predicted, it helps people make important decisions. From this point of view, being able to predict the prices of agricultural products can be used to the benefit of all stakeholders in this field. Making consistent predictions based on historical datasets is a difficult task as it requires modeling both intra-series temporal models and inter-series correlations together. Multivariate time series with multi step and multiple outputs are quite difficult analyze. Conventional statistical analysis like ARIMA, SARIMAX have certain drawbacks in capturing inter series correlations and producing multiple outputs. New perspectives have been employed to solve this problem thanks to the rise of deep learning algorithms. LSTM and CNN are among the mostly researched neural network models in this respect. LSTM model's architectural designs enable it to effectively predict sequence pattern information. CNN model enables filtering input data noise and extract more valuable features that will be more beneficial for the final prediction model (CASADO-VARA et al., 2021). While LSTM networks are designed to handle temporal correlations, they only use the features that are present in the training set, unlike standard CNNs, which are well suited to handle spatial autocorrelation data but are typically not adapted to correctly manage complex and long temporal dependencies (BENGIO et al., 2013).

Graph Neural Network has been the hot research topic in the recent years. It handles input data in graph structure and has been mostly employed in computer vision tasks and social network analysis. There are only few studies in literature that investigate the Graph Neural Networks for time series analysis. And, to our knowledge, it has not been previously applied on price prediction especially in agricultural domain.

In this paper, we curated a new dataset for time series analysis through manually scraping daily market prices and trade volumes of vegetables from the official market website of Turkish Ministry of Commerce (www.hal.gov.tr). A quite new Spectral Temporal Graph Neural Network (StemGNN) has been employed on the dataset which requires multivariate input, multi-step and multiple output time series analysis. Results are compared with CNN, LSTM and RandomForest models. Accordingly, Graph Neural Network achieved state-of-the-art results in all analysis. The main contribution of the paper is that a new time series dataset is publicly presented for the use of scientific research. Another important contribution of the study is that, to authors knowledge, this is the first study that employs Graph Neural Network on Agricultural Time Series analysis. Results of the study indicated the potential of GNN architectures in time series analysis.

Related works

The development of machine learning and deep learning approaches for forecasting price and commodity movements has grown in favor among scientists and business people over the past ten years. These techniques produced some insightful results and findings regarding price behavior. In order to accurately forecast gold prices and movements, LIVIERIS et al. (2020) used CNN and LSTM models. The suggested CNN-LSTM models in two iterations were contrasted with two convolutional layers of cutting-edge deep learning algorithms, each with a different number of filters. In addressing regression-based issues, the CNN model had the lowest MAE and RMSE values and provided the most precise prediction outcomes. The LSTM model, on the other hand, performed better than the conventional time series models in predicting changes in the price of gold.

A multimodal graph neural network (MAGNN) was used by CHENG et al. (2022) to predict financial time series of equities. By employing a two-stage attention mechanism, it was made sure that the final beneficiaries carefully consider the value of internal modality and intermodal resources in order for this way to be properly interpreted. Experiments with real-world datasets have demonstrated that MAGNN is particularly effective in forecasting the financial markets. Investors now find it simpler to make more lucrative investments as a result.

GOPALI et al. (2021) compared LSTM based on recurrent neural networks (RNN) and Temporal Convolutional Networks (TCN) based on CNN models, and their performance and training times are presented. Their experimental findings show that both modeling approaches perform similarly, with TCN-based models marginally outperforming LSTM. Additionally, compared to RNN-based LSTM models, the CNN-based TCN model constructs a stable model more quickly.

Research utilizing deep learning for time series prediction were described in detail by LARA-BENITEZ et al. (2021). Seven distinct deep learning models' utility levels were contrasted. The LSTM and CNN models offered the most precise estimations out of the seven models that were tested. With equivalent performance and less result variability under various parameter setups, CNNs are more effective.

MATERIALS AND METHODS

In this paper, a new dataset has been manually curated from the official site of Marketplace Registration System, which is a state website maintained by Ministry of Commerce of Turkey. The dataset contains daily price and trading volume of green pepper, tomato, pumpkin and cucumber (all conventional products). The dataset covers the period between January 1, 2018 and November 26, 2022, which sums up to 1791 days. The curated dataset and codes of the applied models are shared in the Github repository (https://github.com/cevher/Time-Series-Analysis).

The dataset used in this paper consists of multivariate time series and the problem we try to solve requires the determination of intra-series and inter-series correlations simultaneously in order to forecast multiple target timeseries as outcome. In order to achieve this purpose, dataset is formulated as multivariate temporal graph.

$$G = (X, \bar{X}, Y, \bar{Y}, Z, \bar{Z}, H, \overline{H}, W). X, \bar{X}, Y, \bar{Y}, Z, \bar{Z}, H, \overline{H}, =$$

$$\{X_{it}, \bar{X}_{it}, Y_{it}, \bar{Y}_{it}, Z_{it}, \bar{Z}_{it}, H_{it}, \overline{H}_{it}\} \in \mathbb{R}^{NxT}$$

N is the number of time series (nodes), T is the number of timestamps, x_t, y_t, z_t, h_t are the observed prices and $\bar{x}_t, \bar{y}_t, \bar{z}_t, \bar{h}_t$ are the trade volumes of 4 variables at timestamp t, w, is the adjacency matrix where $w_{ij} > 0$ indicates the presence and strength of an edge between i and j. Given the previous K timestamps of the observed variables, the task is to forecast future node values.

Statistical methods such as ARIMA, SARIMA, ARIMAX and SARIMAX fall short in producing multiple target forecasting. Various machine learning and deep learning methods are being researched in literature for this problem type. CNN, LSTM and RNN based deep learning methods have been used on various time series studies in literature. We have employed Random Forest, CNN and LSTM models on our dataset in order to provide a benchmark. One of the latest hot topic in literature is Graph Neural Networks, which handles input data in Graph structure. Graph Neural Networks (GNNs) are a type of neural network that can process graph-structured data. They have been widely used in various applications such as social network analysis, recommendation systems, and computer vision. In recent years, there has been growing interest in using GNNs for time series analysis, particularly for modeling temporal dependencies in graph-structured data.The basic idea behind using GNNs for time series analysis is to represent the temporal dependencies between different nodes in a graph as edge weights. This allows the GNN to learn how the time series evolves over time by propagating information through the graph. One approach to achieve this is to use a Graph Convolutional Network (GCN) architecture with a temporal convolutional layer, which allows the network to capture the temporal dependencies in the graph.

The overall structure of StemGNN is given in figure 1. The original paper is proposed by the researchers in Microsoft and gives more detailed information about the network (CAO et al, 2020). However, we briefly emphasize the core points and mechanism of the network. The model structure starts with a latent correlation layer, which takes multivariate time-series input and produces associated weight matrix. Next, the graph data obtained from the latent correlation layer is given as input to StemGNN layer that consists of two residual StemGNN blocks. StemGNN blocks models the structural and temporal dependencies among multivariate time series jointly in spectral domain. The sequence of operations in this block is as follows: first a Graph Furrier Transform operator transforms the graph data into a spectral matrix in which univariate time series for each node becomes linearly independent. A discrete furrier transformation is applied to each univariate time series and produces frequency domain. In this domain, each independent layer is fed into 1D convolution and Gated Linear Units (GLU) captures the feature patterns before transforming data back into the time domain through inverse discrete furrier transformation. Then, graph convolution is applied on the produced spectral matrix and inverse graph furrier transformation is performed. Following the StemGNN blocks, an output layer

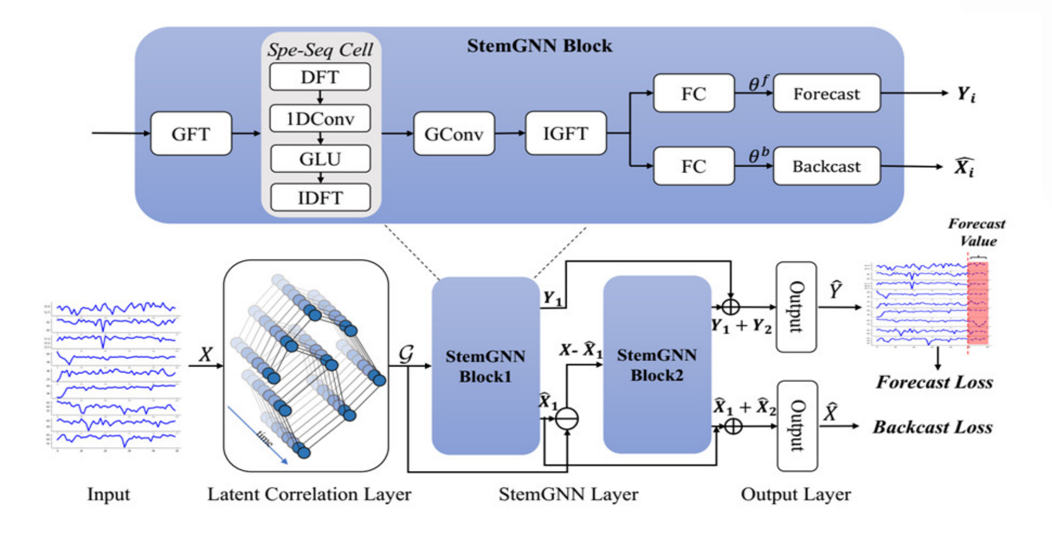

Figure 1 - Structure of the Spectral Temporal Graph Neural Network.

consisting of GLU and fully connected layers produces two types of outputs, which are forecast *Yi* and outputs $\hat{X}_i$ to backstage for increasing the representation of multivariate time series input during training. Time stamps inputs are fed in sliding window and rolling strategy is employed for multi-step forecasting.

We have employed a simple CNN architecture to forecast multi target outputs in this paper. The model consists of Conv1D (kernel size=2), MaxPooling1D (pool_size=2), Conv1D (kernel_size=3), MaxPooling1D, Flatten, Dense (activation=ReLU), Dense (output layer) with adam optimizer and 'mse' loss function. We have trained the network with 200 epochs.

The LSTM model has a simple architecture as well. It consists of LSTM and Dense layers with adam optimizer and 'mse' loss function. We similarly trained the model for 200 epochs.

RESULTS

The dataset contains daily prices and trade volumes of four vegetables that are major vegetable products cultivated in Turkey. The dataset covers a total of 1791 days between January 1, 2018 and November 26, 2022 and has no missing value. Prices and volumes are standardized by min-max scaler for eliminating any possible bias. Only a few outlier values are detected and cleansed from the dataset. First difference of the dataset provided non-stationarity. The dataset before and after taking first difference is shown in figure 2. Then, data is preprocessed into 28 days of 8 columns as input with a utility function. Dataset is separated into 90% training (1612 days) and 10% test sets (179 days). All models are evaluated for 5 days and 10 days multistep forecasts for 4 price outputs.

The evaluation is performed on a computer with Intel(R) Core(TM) i7-7500U CPU, 2.70GHz. Mean Absolute Error (MAE), Root Mean Square Error (RMSA) and Mean Absolute Percentage Error (MAPE) metrics are used to evaluate performances.

x_i,y_i → actual and target count of grains for i^{th} image; N = number of image:

$$\mathrm{MAE} = \frac{\sum_i |x_i - y_i|}{N} \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_i (x_i - y_i)^2}{N}} \tag{4}$$

The most popular metrics for evaluating accuracy for continuous variables are MAE and RMSE. Both metrics are indifferent to the direction of error and can range between 0 and ∞. *The lower scores mean better prediction.*

The evaluation results the models are summarized in table 1. StemGNN outperformed all other models with state-of-the-art results for both multistep forecast periods. StemGNN does not require prior knowledge of data topology and the results demonstrate the feasibility of automatic learning of latent correlations within time series. The drawback of other models is that they cannot establish the correlations among multiple-time series explicitly,

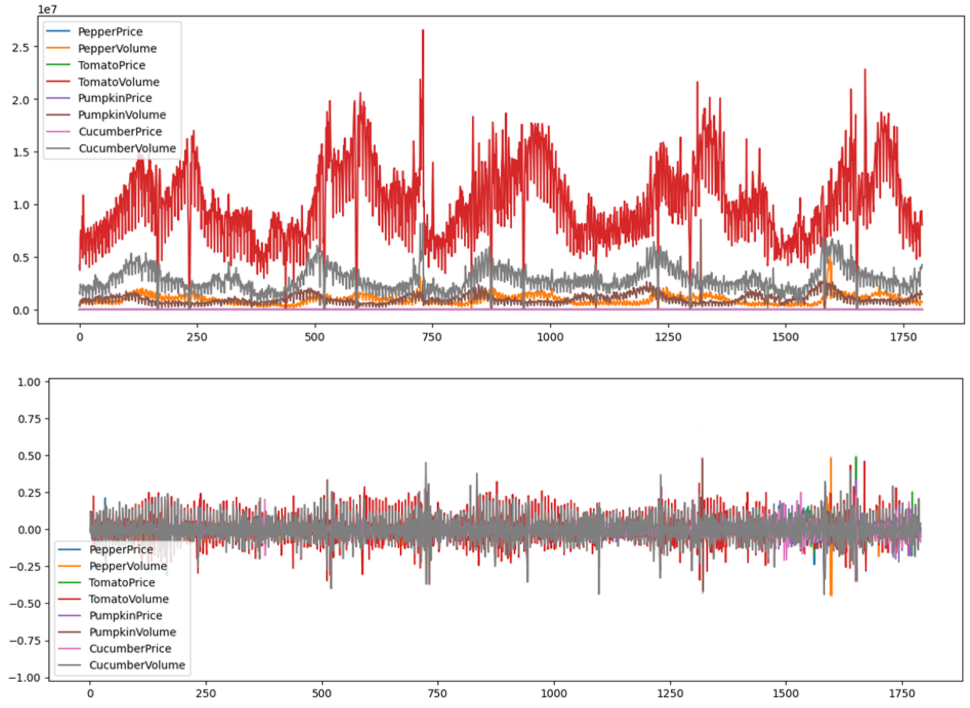

Figure 2 - Before and after pre-processing data.

which limits their performance on multivariate and multi target time series predictions. The results are quite persuasive that data-driven latent correlation layer works better than human defined priors. Similar findings have been reported on traffic prediction, Electricity Consumption prediction and covid-19 case prediction studies. This paper supports these findings and broadens the efficacy of latent layer on agricultural price prediction.

DISCUSSION

This paper investigates the applicability of the latest research hot-topic Graph Neural Networks on agricultural price prediction tasks. Spectral Temporal Graph Neural Network is used for this purpose on a manually collected datasets that consist of multiple inputs and targets. The results of the StemGNN has been tested and compared against the CNN, RandomForest and LSTM models commonly used in literature for solving the same problem type. StemGNN outperformed all other models with both 5 days and 10 days future forecasts. The results demonstrated the efficacy of latent correlation layers included before the StemGNN blocks. This layer enables the capture of both inter series and intra series correlations effectively. There is no study in literature that employs Temporal Graph Neural Network on agricultural price forecast. Therefore, we will give its application on other domains for discussion

Table 1 - Forecasting results for 5 days and 10 days.

	--------------------5 days forecast--------------------		--------------------10 days forecast-------------------	
	MAE	RMSE	MAE	RMSE
Random Forest	3.57	6.16	3.60	6.17
CNN	4.15	6.62	4.42	6.94
LSTM	3.38	5.84	3.39	5.81
StemGNN	1.37	1.94	1.38	1.98

purposes. CAO et al. (2020), a research team in Microsoft, proposed StemGNN model for time series predictions. In their study, they tested the performance of StemGNN against various other models like Fully Connected Neural Network, LSTM and CNN. As a result of their experiments, the researchers emphasized the obvious superiority of the StemGNN model over other models for 7-14 and 28-day predictions. YANG et al (2021) applied the StemGNN architecture to contribute safer flights in the field of civil aviation by processing The Quick Access Recorder (QAR) data with time series predictions. The main purpose of the model is to effectively extract the inter-series correlation and increase the accuracy of accident warning predictions. As a result of their experiments, the authors stated that the StemGNN model gave better results than LSTM and CNNLSTM and that this model could be used easily in civil aviation. In order to do combined orbital sequence modeling and spatial graph convolution modeling in the frequency domain, CAO et al. (2021) suggested SpecTGNN. A tailored version of StemGNN, in order to improve how well embedded orbital data may be used to leverage long-term temporal dependence. The usefulness of the SpecTGNN in predicting pedestrian and vehicle trajectory has been established as a consequence of the comparison of these two models. These findings are consistent with the findings in our study. Based on previous energy usage, KIM & CHO (2019) predicted residential energy consumption using a CNN-LSTM neural network. The CNNLSTM algorithm, which combines convolutional neural network (CNN) and long short-term memory (LSTM), was able to forecast the intricate characteristics of energy consumed in households, according to the experimental findings. The LSTM layer was able to model temporal information regarding the irregular trends in the time series components, while the CNN layer determined the characteristics of various factors influencing energy consumption. A group solar radiation neural network was reportedly suggested by JIAO et al. (2021) to estimate solar radiation. In the research, CNN architecture was used to test data obtained from the US National Renewable Energy Laboratory. In comparison to other estimation techniques, the experimental results indicated that the CNN architecture would have the best accuracy for estimating solar radiation. ENGEN et al. (2021) employed deep learning methods in order to produce a sizable, reusable dataset of farm-scale agricultural yield production that could serve as farm-scale ground truth prediction targets. In order to estimate efficiency, the study compared the results using the DNN, CNN-RNN, and LSTM architectures. The LSTM algorithm produced the best outcomes among the three artificial algorithms in terms of accuracy. In order to forecast wheat yield, SUN et al. (2022) systematically compared various deep learning models in terms of data fusion, time series feature extraction, and multitasking learning. With R^2 values of 0.817 and 0.809, experimental findings demonstrated that time series data aggregation greatly increased the accuracy of wheat yield prediction. Deep learning techniques can be used today in many areas to forecast the future with high accuracy, according to studies in the literature. Especially the LSTM architecture that we used in our study produces effective outcomes. Additionally, we believed that this architecture can be effectively applied to forecast future agricultural product prices. Future studies could investigate the effectiveness of the Temporal Graph Neural Networks with latent correlation layer on different time series analysis fields such as stock price, supply-demand predictions and oil price scenarios.

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DECLARATION OF CONFLICT OF INTEREST

The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

AUTHORS' CONTRIBUTIONS

Cevher Özden: Supervision, conceptualization, investigation, methodology, formal analysis and writing – original & draft;

Mutlu Bulut: investigation, resources and writing – review & editing. All authors critically revised the manuscript and approved of the final version.

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