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Prediction of Rice Yield via Stacked LSTM

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ABSTRACT

In order to guarantee the rice yield more effectively, the prediction of rice yield should be taken into account. Because the rice yield every year can be seen as a sequence of time series, many methods applied in prediction of time series can be considered. Long Short-Term Memory recurrent neural network (LSTM) is one of the most popular methods of time series prediction. In consideration of its own characteristics and the popularity of deep learning, an improved LSTM architecture called Stacked LSTM which has multiple layers is proposed in this article. It is based on the idea of increasing the depth of LSTM. The comparison among the Stacked LSTM architectures which have different numbers of LSTM layers and other methods including ARIMA, GRU, and ANN has been carried out on the data of rice yield in Heilongjiang Province, China, from 1980 to 2017. The results showed the superior performance of Stacked LSTM and the effectiveness of increasing the depth of LSTM.

KEYWORDS

Depth, Long Short-Term Memory, Time Series

INTRODUCTION

Rice is one of the most important food sources for more than half of the world's population (Jeon et al., 2011), it is the second most widely grown cereal crop worldwide (Hirooka et al., 2018) and the demand for rice is expected to grow because of the increasing population on earth (Daniela et al., 2018). In order to ensure the rice yield keeping up with the pace of population growth, some measures to guarantee sufficient rice supply, in other words, food security, are needed necessarily. Crop yield prediction is a representative measure which is vital for food security (Hutchinson, 1991). It can obtain the result whether the future crop yield can achieve the demand of population, therefore, it plays a key role in government's policy making and preparing production plan for following year. Proper decisions of government based on crop yield prediction can make more efficient management of crop production processes. On the other hand, crop yield prediction can provide a reference for farmers and enterprise, thus helping them increase outcome (Na-Udom & Rungrattanaubol, 2015), so rice yield prediction is a matter of importance.

Crop simulation models are used extensively, simulation of plant-growth stages and consequently forecasting the crop yield permits better planning (Inoue, Susan & Horie, 1998). Crop growth

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simulation model are combined with remote sensing data to estimate rice yield (Abou-Ismail, Huang & Wang, 2004; Inoue, Susan & Horie, 1998). N. Pirmoradian et al. (2006) proposed a very simple model(VSM) to predict rice grain and biomass yields. But the application scope of crop growth models is a little limited, they may only adapt to a few crop species. Meanwhile, the development time and cost of these models are extremely large (Alberto, Juan & Waldo, 2014). Many statistical methods are also used for yield prediction in early stage, such as Multiple Linear regression, logistic regression (Cakir, Kirci & Gunes, 2014), which eliminate the limitation of application range. Liu Qin-pu (2011) proposed grain yield spatio-temporal regression prediction model of Henan Province; Umid Kumar Dey et al. (2017) applied Multiple Linear Regression AdaBoost to the task of predicting rice yield in Bangladesh. R. K. Pal (2012) developed the multiple regression equations for prediction of growth and yield attributes of wheat. The complicated relationships between crop production and interrelated factors cannot be described well by statistical models (Cakir, Kirci, & Gunes, 2014). Due to the aforementioned shortcomings of traditional models, many methods based on machine learning are inspired to solve yield prediction tasks recently. Ratchaphum Jaikla et al. (2008) used the Support Vector Regression method to predict rice yield and acquired comparable performance with Crop Simulation Model. Artificial neural networks (ANN) is a popular method used in crop prediction. For example, Yüksel Çakır et al. (2014) used ANN to predict wheat yield in south-east region of Turkey; Niketa Gandhi et al. (2016) applied ANN with multilayer perceptron to rice yield prediction from year 1998 to 2002 in India.

In general, rice yield data can be considered as a sequence of time series, so the prediction of rice yield can be implemented by time series predicting methods (Chen, Qi, Yuan, & Li, 2018). Due to the intra-layer nets are connectionless in the architecture of traditional neural network, it results in bad performance in dealing with problems of time series. Long short-time memory recurrent neural network (LSTM) is a novel but effective method to deal with time series. LSTM is designed to overcome the problem of vanishing/exploding gradient in Recurrent Neural Network (Hochreiter & Schmidhuber, 1997) and can learn to store input information for a long time (Lecun, Bengio, & Hinton, 2015). It yields excellent performance on processing sequential data. To the best of our knowledge, there is little research about applying LSTM to crop yield prediction, so this paper attempts to explore potential of LSTM in processing crop yield prediction problems. Due to the recurrent nature in the architecture of LSTM, it is deep essentially. It inspires discussion about whether LSTM can get more effective performance by deepening the depth of the network architecture. In this paper, an improved LSTM architecture called Stacked LSTM which deepens the network by adding layers on the basis of 1-layer LSTM is proposed to address task of rice yield prediction. After comparing with 1-layer LSTM and several other methods of prediction, Stacked LSTM has been found that achieved superior prediction performance.

The remaining paper is structured as follows. Section 2.1 illustrates data acquisition and preprocessing, Section 2.2 describes the specific theory of LSTM and Stacked LSTM, the evaluation methods are also described in this section. Section 3 will discuss research results achieved by comparing Stacked LSTM with 1-layer LSTM, ARIMA, GRU, ANN. Finally, Section 4 will give conclusion of this paper.

MATERIALS AND METHODS

Data Acquisition and Preprocessing

The data of rice yield available in this work have been obtained from the year 1980 to 2017 in Heilongjiang Province, China, from the website of Heilongjiang provincial bureau of statistics. In total, there are 38 records, thereof none with missing values and none with outlier. Because the rice yield data follows a rising trend obviously, it was transformed into stationary time series through difference processing first. Note that, before using LSTM model, the data should be transformed into supervised learning problem. The data used here is shown in Table 1.