[1] La mayoría de los sistemas de agua continúan sus operaciones utilizando la demanda instantánea. Se construyeron dos modelos con los algoritmos SVM como técnica de regresión y ARIMA. Como datos se utilizaron consumo de agua y crecimiento de población. Se busca predecir la demanda de agua y comparar con el consumo de agua. SVM mostró mejores resultados que SVM. Se usaron RMSE y MAPE como métricas de evaluación.

[2] The statistical theory method is the earliest forecasting method. The urban water supply forecast models based on this method mainly includes time series analysis [7], regression analysis [8], and autoregressive integrated moving average [9]. With the rapid advancement of computer technology, the forecast models with various artificial intelligence algorithms have continuously emerged, such as artificial neural network [10], support vector machine [11], random forest [12], recurrent neural network (RNN) and its variant long short-term memory (LSTM) [13]. Among them, the LSTM network is currently the most important time series forecasting model. Given that the unit state is added in the hidden layer to save the preserved information of the historical time, the temporal characteristics of the data can be fully considered [14], [15]. The LSTM-based model can extract important features at a deeper level, thus solving more complex forecast problems than the traditional statistical theory.

Procesamiento de datos: the max-min normalization method was employed to standardize the data set.

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Description automatically generated

Se utilizó LSTM / CNN-LSTM / LSTM-AM / CNN-LSTM-AM , que van de peor a mejor. De R2 0.896 a 0.93.

CNN-LSTM

[1] Este estudio utilizó temperatura y precipitación mensual promedio de 1961 al 2018, y NDVI (variable de interés) mensual también.

[2] Classic time-series techniques such as multilinear regression and the well-known Auto-Regressive Integrated Moving Average (ARIMA) have been applied for gold price prediction problem [2, 12, 20]. Besides the classic econometric and time-series approaches, various machine learning methods are utilized to mining the inner complexity of gold price [10, 17, 18, 21, 28]. Nevertheless, the statistical methods usually require assumptions such as stationarity and linear correlation between historical data, while the more sophisticated machine learning methods seem to fail to identify and capture the nonlinear and complex behavior of gold price time series. As a result, all these methods cannot guarantee the development of a reliable and robust forecasting model.

Long short-term memory (LSTM) networks and convolutional neural networks (CNNs) are probably the most popular, efficient and widely used deep learning techniques [11]. The basic idea of the utilization of these models on time-series problems is that LSTM models may efficiently capture sequence pattern information, due to their special architecture design, while CNN models may filter out the noise of the input data and extract more valuable features which would be more useful for the final prediction model. However, standard CNNs are well suited to address spatial autocorrelation data, they are not usually adapted to correctly manage complex and long temporal dependencies [4], while in contrast LSTM networks although they are tailored to cope with temporal correlations, they exploit only the features provided in the training set. Therefore, a time-series model which exploits the benefits of both deep learning techniques could improve the prediction performance.