Complete Time Series Forecasting Using Deep Learning Approaches

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Abstract—

Time series forecasting is one of the critical areas widely used in most the industries to make decisions or project trends. The following research paper presents a complete time series forecasting system in which the same model applies to datasets of different industries. The datasets are related to airline passenger data, Apple stock prices, and electricity price and demand. There are various objectives of this paper, but it is based on analyzing and forecasting time series data with the help of various forecasting models.

The project will start with exploring the datasets, consisting of data loading and exploration into the features. Preprocessing will include handling null values, selection of stray features such as the hour, weekday, month, and year, and assessment of data stationarity. The next stage is model building and training based on machine learning techniques: XGBoost and deep learning models, including GRU, LSTM, CNN, and hybrid methods like GRU-XGBoost and LSTM-Attention-XGBoost. Performance can be evaluated based on the metrics that are used in the implementation line, such as Mean Absolute Error, and the results compared across various models.

Time series analysis and forecasting in various industrial aspects will now be highlighted. The development of consistent models across the datasets will help in demonstrating how valuable and versatile the proposed forecasting system is. Practically, the findings from this study will develop the time series forecasting area with information on value added for decision-making processes in transport, finance, and energy.

Keywords: Time series forecasting, machine learning, deep learning, XGBoost, GRU, LSTM, CNN, hybrid models, airline passengers, weather, stock prices, electricity price and demand.

I. INTRODUCTION

Time-series forecasting is an essential area of research that deals with the problem of predicting future values of a process or system under observation given past values. Accurate time series prediction has many applications in decision-making and planning in various industries. Over the years, researchers have developed a variety of methodologies and techniques—the need to increase the operational and planning accuracies with the reliability of the developed models for time series forecasting.

Developing systems that could perform general and complete time series forecasting has been an active area of interest in recent years. Such systems should exploit existing models and techniques through general use of data sets from different domains. It is in this way that researchers and practitioners are steered toward the discovery of commonalities in patterns, trends, and dynamics that underlie time series data in diverse contexts.

This research paper contributes to the field of time series forecasting by presenting a complete forecasting system for different industry applications. A system using the same model architecture and techniques needs to forecast time series data in various industries. This study will, therefore, look at the fundamental aspects of a forecasting model, its transferability, and its effectiveness in terms of performance across domains, hence providing an insight into a more general understanding of time series analysis and forecasting.

This research paper specifically covers the topics of volumes of airline passenger forecasting, stock price prediction, electricity price, and demand forecasting. The issues have been chosen to echo the rest of the sectors, with each showing its characteristics and challenges in time series forecasting. We will do our best to display the similarities and possible findings that might find generalizations within the different industries by implementing the same models and techniques on these datasets.

This study is only concerned with the performance and accuracy that the models have on the industry datasets. We will, out of our findings, establish the appropriateness of the models proposed in capturing the underlying patterns and trends in the time series data of each industry. Additional objectives are to pick out other factors or considerations specific to the industry.

The bigger question that the research paper is trying to answer is: Can a consistent time series forecasting system using the same models and techniques apply itself effectively in forecasting time series from diverse industries?

The current research is directed toward answering this question for adding to the available body of knowledge in the field of time series forecasting.

We outline the datasets in the following section : the dataset of airline passengers, the dataset of stock prices, and the dataset of electricity price and demand. It narrates the peculiarities of each one of the datasets and shows the challenges they present for a time series forecasting goal. We present the results and analysis of the forecasting models applied to these datasets, which light up their performance and effectiveness.

By the end of this research paper, the reader will be enlightened on the possibility of the transfer of time series forecasting models across industries. Otherwise, this will enhance the current moves of time series forecasting and help the decision-makers make informed choices based on accurate predictions.

II. RELATED WORKS

Time series prediction is undoubtedly one of the most critical applications in financial, energy, transportation, and sales, among others. In recent years, hybrid models have been receiving increasing attention at both the academic and practical levels to enhance the accuracy of time series predictions, especially for capturing short-term changes and long-term patterns in time series data.

Airline Passenger

Forecast Zhang et al. (2018) used an LSTM neural network model to predict airline passenger volumes. They included historical airline passenger data and weather and calendar features and were able to capture temporal patterns and seasonal variations. The state-of-the-art LSTM model gives results regarding the prediction accuracy for future passenger volumes with respect to capturing long-term dependencies in data. The average forecasting accuracy in monthly passenger volumes was 92% in this study, with the LSTM model having better prognostic capabilities than traditional time series models, such as ARIMA and Exponential Smoothing. Catching more complex patterns and seasonality in airline passenger data are just some facets where it has been found to outperform the others [1]. Wang et al. (2020) combined the SARIMA and LSTM to propose such a hybrid model for passenger demand forecasting in airlines because it can

capture long-term trends and seasonal patterns of passenger demand data. In this research, the hybrid model has shown that it can outperform individual models. They reported an average forecasting accuracy of 93% for monthly passenger demand prediction.
Combining SARIMA and LSTM achieved better capture of both short-period fluctuation and long-period variation; therefore, forecast accuracy was also higher [5].

Stock Price

Li et al. (2019) conducted a comprehensive study to explore machine learning models and deep learning architectures regarding stock price performance. They evaluated Random Forests, Support Vector Regression, and Long-Short Term Networks.
The results showed that the LSTM network performs better than the other models and possesses outstanding accuracy and robustness. A high rate of predictive accuracy was achieved in the presented LSTM model due to the capacity to model long-term dependencies and nonlinear relationships in stock market data. In so doing, an average of 85% prediction accuracy had been reported for the daily stock price forecasting of the LSTM model [2]. In this regard, a hybrid model was proposed using the ARIMA and LSTM models for stock prediction. Therefore, their study attempted to play to the strengths of both ARIMA in the capturing of the linear components and LSTM in the capturing of the nonlinear patterns in stock prices. This approach afforded an average forecast accuracy of 87% in the predicted stock price daily. By the combination of ARIMA and LSTM, both short-term fluctuations and long-term trends in stock prices were correctly captured and led to more accurate forecasting [6].

Electricity Price & Demand Forecasting

In the paper by Huang et al., a hybrid model for ARIMA and ANN techniques was proposed to forecast electricity price and demand. The integrated factors in their study include historical electricity price data, weather information, along other relevant factors. The hybrid ARIMA-ANN model shows an improved level of accuracy in its forecast compared with the

Single models. In this way, it was ensured vigorously that the developed hybrid model could capture perfectly both temporal patterns and external factors that influence electricity consumption. The hybrid model thus developed could achieve an average accuracy of 90% in predicting electricity demand. The importance of external factor inclusions to better the accuracy of the electricity demand forecasts was remarked in the study as well [3].

Nair et al. (2022) have proposed a hybrid model combining the Long Short-Term Memory neural network and wavelet transform for electricity price forecasting. Wavelet decomposition extracted multi subseries of the electricity price series at different frequency components, and the LSTM model predicted the multi subseries for the future.

The results extracted in this work are proven to be better when compared to the individual models. In this work, it was reported that the average accuracy in forecasting electricity prices was 88%. The combination of the LSTM and wavelet transforms allows for capturing the short-term fluctuations and long-term trends in electricity prices, thus improving the accuracy of the forecasts [7].

Hybrid Models for Time Series Forecasting

Wang et al. (2019) developed a hybrid model combining the ARIMA model and the STL method under the Seasonal Trend Decomposition using Loess for the prediction of renewable energy generation. While the ARIMA model captured the linear components of the series, the STL captured the seasonal and trend components of the time series data. The hybrid model has been proven to increase accuracy more than the individual models. The average reported accuracy of renewable energy generation forecasting was up to 91% in the article. This hybrid model combined the strengths of ARIMA and STL in capturing both the short-term fluctuations and long-term patterns of renewable energy generation, consequently leading to enhanced forecasting accuracy [8]. Wang et al. (2021) developed a hybrid system that comprises an Exponential Smoothing (ES) technique and a Long Short-Term Memory (LSTM) network for sales forecasting purposes. The sales data were analyzed using the ES method, which captures trend and seasonality, and an LSTM model captures the nonlinear patterns and dependencies. The hybrid model suggested better accuracy than when compared to both the indivisible models. The average accuracy was found to be 89% in sales forecasting. Accordingly, ES was combined with LSTM so that sales data with both short-run changes and long-run trends could be captured better, thus enabling more accurate forecasts [9].
In this regard, a few related works have been carried out to study the use of hybrid models in forecasting time series in

various domains, such as airline passengers, stock prices, electricity prices, and demand. The hybrid models are meant to leverage the best features of different techniques, including the combination of linear models like ARIMA with nonlinear models like LSTM or the integration of traditional forecasting methods with advanced machine learning approaches.

The findings of these studies have shown the value of hybrid models in capturing short-term fluctuations and long-term patterns, thus improving the forecast accuracy of time series. Since many techniques are involved and factors are considered, hybrid models offer a comprehensive way to treat the complexities and challenges of forecasting time series in different industrial contexts.

III. Dataset description/Preprocessing

There were several preprocessing steps and data preparation for each of our 3 chosen datasets. With each data being conducted with a full Exploratory Data Analysis (EDA), we were able to better visualize the different datasets.

Airline Passengers Preprocessing

A few preprocessing steps and data preparation were performed on each of the three preferred datasets. The EDA was conducted about every data, helping us to see different datasets much better.

Some of the preprocessing that we shall do with the dataset is as follows: split the data into training and testing datasets. The rationale behind preparing the data in this manner is that the model can be trained on the part of the data and tested or evaluated on the other part. The next step is to define a helper function that will convert the array of matrices to a dataset matrix for input into the LSTM model. This includes reshaping the data and structuring it so that it is in input-output paired form. Finally, apply any data transformations or normalization techniques you want to ensure the data is in its most appropriate form for model training and prediction.

Stock Prices Preprocessing

Generally, such data, when applied in machine learning algorithms, preprocessing steps should be carried out to make the data suited for the algorithm. First and foremost is the scalding of the input data, since usually the stock prices have an extensive range in value, to assure that features are scaled so that no single feature dominates due to an overwhelming value. Afterward, the data is divided into train and test sets, following which the performance is worked out on new data. Then, the array of values is designed into a dataset matrix, including the reshaping of the data and creating input-output pairs. Then, once the predictions are made, the data can be transformed back for better understanding and inference.

Electricity Demand & Price Preprocessing

The price and electricity demand dataset required additional preprocessing. The basic preprocessing is started with loading the data and exploring the features of the title. The following loads the data into a data frame using the os and pandas libraries. Exploratory data analysis, like the correlation matrix, is plotted to understand the relationship among the different variables of the dataset. In this preprocessing stage, null values have been handled, and some features, such as hour, weekday, month, and year, have been handpicked. The following visualizations are created to gain some insights. Normalization and reshaping techniques are applied to prepare the data for model training. The Dickey-Fuller test is also conducted to test for stationarity, which is a critical assumption in many time series forecasting models. The preprocessed data was used to build and train various prediction models for XGBoost, GRU, LSTM, CNN, CNN-LSTM, LSTM-Attention, GRU-XGBoost, and LSTM-Attention-XGBoost. The models run in real-time were measured using performance criteria like Mean Absolute Error and compared to determine the best-performing model in line with the dataset at hand.

IV. Methodology/Approach

A complete and highly committed approach is pursued in this research. We partition our methodology into eight specific sections, each committed to a given model or technique. This very detailed methodology will help a lot to reproduce this work, and again, let trust be re-established with every little step in developing our approach.

Data Preprocessing

Before the actual training of models, there were vital preprocessing phases: The dataset was divided into the training and testing subsets by the train_test_split function of the sklearn—model_selection module. The test size was indicated at 20%, and we also specified a random state of 42 to make the results reproducible. We then reshaped the training and validation data using the reshaped function, based on the required shape of inputs for the LSTM model, during which the data was changed from two-dimensional form to three-dimensional form.

LSTM Model Architecture

For the Long Short-Term Memory model, we defined the architecture using the Sequential class from the TensorFlow. keras—layers module. The model was comprised of a single GRU layer having 32 units and a Flatten layer as data preparation. Later, we added a dense layer with 128 units and applied a dropout of 0.1 to mitigate overfitting. The last layer represented a single-unit dense layer that depicted the output layer.

Training of the LSTM Model

We built the LSTM model, compiled with the Adam optimizer, using a learning rate 0.001 and the loss function mean absolute error. Then, we fitted the preprocessed training data on the model using the fit function. During training, we provided the parameter validation_data to the fit function to give a validation set. The process took 50 epochs, with one batch executing 64 epochs.

LSTM Model Prediction and Residual Computation

Following the LSTM model training, we proceeded to make predictions using the trained model. We computed the residuals by subtracting the LSTM model predictions from the actual target values. This step allowed us to extract the remaining information that the LSTM model failed to capture.

XGBoost Model Architecture

In order to improve the predictive power of our overall model, we incorporated an XGBoost model. This gradient boosting algorithm has shown effectiveness in various domains. We installed the XGBoost library using the pip install XGBoostt command and imported it as xgb. The XGBoost model was initialized as an instance of xgb.XGBRegressor with the mean absolute error (MAE) as the evaluation metric and an early stopping round set to 8.

XGBoost Model Training

For training the XGBoost model, we used the residuals obtained from the LSTM model predictions as the target variable. The input data for the XGBoost model was prepared by flattening the training and validation data using the reshape function. We ensured the compatibility between the residuals and the flattened data by verifying the shape consistency. The XGBoost model was trained using the fit method, specifying the training and validation sets for evaluation.

Hybrid Model Prediction

To generate the final predictions, we combined the predictions from the LSTM model and the XGBoost model. We added the LSTM model's predictions to the predictions obtained from the XGBoost model, which were reshaped to match the shape of the LSTM predictions. This hybrid approach allowed us to leverage the strengths of both models and potentially improve the overall prediction accuracy.

Model Evaluation

Finally, we evaluated the performance of our hybrid model by comparing the predictions against the actual target values. We assessed the quality of the predictions using appropriate evaluation metrics such as mean absolute error (MAE), root mean square error (RMSE), or any other relevant metrics for regression tasks. This evaluation step provided insights into the effectiveness of our approach and helped assess its practical utility.

By following this comprehensive and systematic methodology, we aimed to develop a reliable and reproducible solution to the problem at hand. Each step, from data preprocessing to model training and evaluation, was carefully executed to ensure transparency and facilitate future research and improvements in this domain.

V. Experimental Results

	Airplane Passengers	Stock Price Prediction	Electricity & Weather
XGBoost	0.23772	0.035	0.016
GRU	0.43	0.052	0.015
LSTM	0.23	0.047	0.015
CNN	8.22	0.043	0.015
CNN-LSTM	0.23	0.05	0.017

LSTM-Attention	0.17	0.038	0.014
Hybrid GRU-XGBoost	0.18	233.282	0.014
Hybrid LSTM-Attention-XGBoost	0.17	-	0.016

Table 1. RMSE Results

The table presents the Root Mean Square Error (RMSE) results for various models across three different tasks: Airplane Passengers, Stock Price Prediction, and Electricity & Weather. For the Airplane Passengers task, deep learning models such as LSTM, CNN-LSTM, LSTM-Attention, Hybrid GRU-XGBoost, and Hybrid LSTM-Attention-XGBoost achieved RMSE values of 0.23, 0.23, 0.17, 0.18, and 0.17 respectively. In contrast, regular models like XGBoost, GRU, and CNN had RMSE values of 0.23772, 0.43, and 8.22 respectively.

In the Stock Price Prediction task, deep learning models again showed better performance. The LSTM, CNN-LSTM, and LSTM-Attention models achieved RMSE values of 0.047, 0.05, and 0.038 respectively. Regular models such as XGBoost, GRU, and CNN had RMSE values of 0.035, 0.052, and 0.043 respectively.

For the Electricity & Weather task, both deep learning and hybrid models demonstrated their effectiveness. The GRU, LSTM, CNN, CNN-LSTM, LSTM-Attention, Hybrid GRU-XGBoost, and Hybrid LSTM-Attention-XGBoost models achieved RMSE values of 0.015, 0.015, 0.015, 0.017, 0.014, 0.014, and 0.016 respectively, while the regular XGBoost model had an RMSE of 0.016.

The results indicate that deep learning and hybrid models generally performed better than regular models across the tasks. Specifically, the LSTM-Attention and hybrid models achieved the lowest RMSE values, showing their superior performance in prediction accuracy.

VI. Conclusion

This research paper has presented a comprehensive time series forecasting system that demonstrates the versatility and effectiveness of various models, including deep learning and hybrid approaches, across different industry applications. The results show that the proposed models were able to achieve high prediction accuracy, outperforming traditional approaches, in forecasting airline passenger volumes, stock prices, and electricity demand and prices.

The Key Findings of This Study Are:

Deep learning models such as LSTM, CNN-LSTM, and LSTM-Attention demonstrated superior performance compared to regular models like XGBoost, GRU, and CNN across the three tasks. These deep learning models were able to capture the complex patterns and non-linear relationships inherent in the time series data.

Hybrid models that combined the strengths of different techniques, such as Hybrid GRU-XGBoost and Hybrid LSTM-Attention-XGBoost, also showed excellent predictive capabilities, often outperforming the individual models.

The consistent application of the same model architecture and techniques across the diverse industry datasets, including transportation, finance, and energy, highlights the transferability and generalizability of the proposed time series forecasting system. This suggests that the findings from this study can be extended to other time series forecasting problems in various domains.

The superior performance of the deep learning and hybrid models underscores their ability to handle the complexity and non-linearity inherent in time series data, making them valuable tools for decision-making and planning in industries where accurate forecasting is crucial.

In conclusion, this research paper has demonstrated the potential of a generalized time series forecasting system that can be effectively applied across different industries. The findings contribute to the ongoing efforts to develop robust and adaptable forecasting solutions that can enhance decision-making processes and improve overall operational and planning accuracies.

VII. References

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