# Comparative Analysis of ARIMA and Deep Learning Models for Time Series Prediction

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Abstract: Time series analysis is crucial for forecasting future trends across various complex real-world domains, including finance, healthcare, and energy management. This study evaluates the performance of traditional and deep learning approaches for time series prediction, comparing the autoregressive Integrated Moving Average (ARIMA) model with Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) architectures. ARIMA, which is designed for linear and stationary data, was tested on the Corona Virus Disease (COVID)-19 dataset to predict infection rates. While ARIMA achieved reasonable success, its limitations became apparent in handling non-linear data. Conversely, RNN and LSTM models excelled in capturing complex non-linear patterns and temporal dependencies, demonstrating superior performance in forecasting a large-cap stock dataset. The experimental results revealed that LSTM significantly outperformed ARIMA in prediction accuracy. This underscores the growing need to integrate statistical models like ARIMA with deep learning techniques to enhance time series forecasting. The findings are particularly relevant for forecasting applications across industries, suggesting that hybrid models, which balance interpretability with predictive performance, may offer the most effective solutions.

## 1 INTRODUCTION

Time series analysis is a basic statistical and computational process for detecting statistics about sequences of data points that have been all obtained in successive details with specific spans. However, it is very important in many applications such as finance, meteorology energy management, and healthcare for a better understanding of hidden behaviors behind real-world data series that may help to predict future trends leading to good decision-making (Torres et al., 2021). Time series analysis is primarily used to analyze data, identify trends, and predict future outcomes by considering the dependencies that exist over time. Time series theories are natural phenomena from over time, that help in linear predictions by defining human pattern characteristics on monthly and seasonal turns through models like Auto Regressive Moving Average (ARMA) & Seasonal Auto Regressive Integrated Moving-Average (SARIMA). Even for simple scaling, they still face difficulty at times to accommodate high non-linearities and data that exhibit complex patterns, especially in the presence of higher dimensions or if the system is not stationary (Lim and Zohren, 2021).

With growing complexity of data, innovation is the call-to-action for this new kind of modern time series data and work. Consequently, numerous studies are prompting more sophisticated algorithms to develop where machine learning and deep learning are combined. Overall, this work has demonstrated an ability to address the constraints of traditional models by offering more sophisticated predictive performance as well as enabling new rules on architecture and data format. Hence, the study of time series analysis techniques is indispensable and important in both research and numerous real-world applications (Shen et al., 2020).

The area of time series analysis has made very strong marks recently, notably in the era when machine learning and deep-learning techniques rule. Among the traditional methods, ARMA and SARIMA are still widely used for their simplicity to implement quickly, yet they perform well on some time series datasets. They are well-suited for linear,

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stationary data and renowned for their interpretability (Sezer et al., 2020). However, the efficiency of Recurrent Neural Networks (RNNs) declines in tackling nonlinearity, long-term dependencies as well as high-dimensional data.

In response to these challenges, researchers are more frequently using deep learning models such as RNNs and Long Short-Term Memory (LSTM) networks. Since sequence data can be serialized in time, RNN comes up with stronger performance at modeling temporal patterns. LSTM networks are one type of RNN more designed for long-term dependency communication and bypass the standard neural network training issue caused by gradient decay (Zeng et al., 2023). These models have demonstrated state-of-the-art performance in various applications, including stock market prediction, weather forecasting, and natural language processing, by effectively capturing the complex, non-linear relationships present in data. More recently, it has been seeing a rise in interest starting to use new methods such as Graph Neural Networks (GNNs) and Transformer models for time series analysis (Satrio et al., 2021). GNNs are especially useful for encoding features of nodes in the graph since they model node dependencies (social networks or financial interconnected systems) through structural properties (Mao and Xiao, 2019). Transformer models, designed for originally the Natural Language Processing (NLP) domain have also shown great promise in time series forecasting modeling large datasets efficiently, and capturing long-range dependencies (Zeng et al., 2023). Insight into what these cutting-edge models mean for time series analysis and how new advancements can be used to predict more accurately, as well as glean actionable insights from the data.

This study aims to systematically review foundational technologies for analyzing time series data, addressing a gap in comparative analysis and methodological connections. The paper provides a thorough review of evolving paradigms in time series analysis, outlining major philosophies and distilling key concepts to assist beginners re-entering the field. It also offers insightful perspectives on methodologies designed to handle increasingly complex high-dimensional non-linear data. The study highlights successful applications of these technologies through real-life case studies, detailing their benefits and limitations. Additionally, it provides a brief overview of future trends and potential research directions. By synthesizing current methodologies and exploring practical applications, this paper aims to enhance understanding and guide future investigations in time series analysis.

# 2 METHODOLOGY

## 2.1 Data Modeling and Analysis Principles

This research applies two primary methods for time series prediction: the classical ARIMA model and modern deep learning techniques such as RNNs and LSTMs. ARIMA model, useful for linear and stationary data, uses auto regression, differencing, and moving average techniques for forecasting. Meanwhile, its major advantage of being easily interpretable, the application of ARIMA for analysis of non-linear and non-stationary data reduces its efficiency. On the other hand, RNNs especially LSTMs-are categories of neural networks introduced to model and depict non-linear processes in the temporal data. Such structures as memory cells make LSTMs ideal for temporal forecasting due to the ability to capture long-term dependencies. This work discusses the performance of both ARIMA and LSTM models when applied to different datasets and different situations. A described flowchart of the methodology pipeline for this research is provided in Figure 1 below.

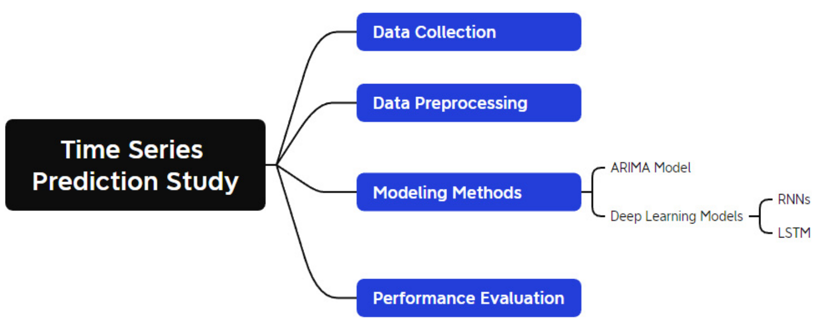


Figure 1: The time series prediction study pipeline (Picture credit: Original).

## 2.2 ARIMA Model

### 2.2.1 Dataset Description

The ARIMA model was applied to a dataset tracking the spread of the Corona Virus Disease (COVID-19) epidemic, sourced from Johns Hopkins epidemiological records. This dataset includes time-stamped information on infection rates, recoveries, and other pandemic-related statistics. It is particularly suited for ARIMA, which requires stationary time series data for effective prediction. The goal is to predict the incidence and prevalence of COVID-19 over time, leveraging ARIMA's ability to model and forecast linear trends in the data. This dataset is described in the study Application of the ARIMA model on the COVID-2019 epidemic dataset (Benvenuto et al., 2020).

### 2.2.2 Core Technology

The ARIMA is a common statistical model in analyzing time series data especially when the series is linear and stationary. It integrates three components. First, Auto-Regressive (AR) Component – this part describes the connection between an observation and certain previous observations (or earlier time points). Next, the Integrated (I) Component is the differencing of raw observations to render the time series stationary. This step helps in the removal of trends which helps in making the model trendless by focusing on variations around the mean. Lastly, the Moving Average (MA) Component, this part captures the dependence of an observation on the residual errors from a moving average model of lagged observations.

For this application, ARIMA requires the tuning of three parameters: p stands for the order of the AR term, d for the degree of differencing, and q for the order of the MA term. These parameters are normally selected from statistics on model performance on the validation data using statistics such as the Akaike Information Criterion (AIC). Even though the ARIMA model is quite easy to apply, there are restrictions as it cannot handle non-linearity which is often found in the real time data sets and especially when exposed to shocks like the COVID-19 Pandemic (Benvenuto et al., 2020).

## 2.3 RNN and LSTM Models

### 2.3.1 Dataset Used

For the RNN and LSTM models, a stock market dataset was utilized, which captures historical stock prices over time. This dataset is highly volatile, with stock prices influenced by a variety of external factors, making it ideal for testing the ability of deep learning models to capture complex, non-linear dependencies. The dataset includes time-stamped records of stock price movements, which allow the models to learn temporal patterns and make future price predictions. This dataset is explored in detail in Predictive Data Analysis: Leveraging RNN and LSTM Techniques for Time Series Dataset (Agarwal et al., 2024).

### 2.3.2 Core Technology

RNNs are special types of neural networks that are used to work with sequences of data. Neural networks work beyond others in series where inputs are processed independently from each other whereas RNNs take feedback of the output and pump back into the network. This looping mechanism empowers RNNs to grasp temporal dependencies. Nonetheless, RNNs face serious challenges, notably the vanishing gradient problem where gradients reduce as they are back-propagated through time making it hard for the model to learn long term dependencies.

Therefore, to solve the vanishing gradient issue, an LSTMs architecture is recommended. To overcome this challenge, LSTMs have a memory cell reserved for the whole sequence. This is by an input gate which determines what information with regard to the inputs should be used in updating memory. Another known type is the forget gate which determines which parts of the cell states it needs to remember or forget and the output gate or the pseudo-gate which has a similar function to patterns of what it wants to reveal along with the final results. This enclosed structure allows LSTM to maintain the information that is important, and discard the rest, for long periods, and is ideal for assessing future values from a long range of previous and current values. In the stock market application, LSTMs perform much better than traditional RNNs and other models since LSTMs address the vanishing gradient problem inherent in highly volatile time series data while incorporating the long-term dependencies. In one application, LSTM was found to predict with an accuracy of 91.97% was achieved on testing data (Agarwal et al., 2024).

The integration of these two models means that researchers can take the best of conventional statistical methods and modern deep learning and apply them to improved time series prediction in various situations.

# 3 RESULT AND DISCUSSION

## 3.1 The Performance of Models

As indicated in Table 1, the two techniques; ARIMA and RNN/LSTM provide somewhat different results in terms of time series prediction. The accuracy of the ARIMA model was high not only in the case of short periods of observations but also in cases of relatively simple and linear data, such as the dynamics of COVID cases. But when having to deal with more complex and non-stationary data like the stock market data, the accuracy of the ARIMA method is reduced. When the nature of the data was more volatile and complex, the errors made in prediction also tended to rise. Conversely, based on the nature of the RNN-LSTM model, which was created to handle non-linear and more complex trends, the model yielded significantly more accurate long-term predictions, especially, if the data set was intrinsically volatile. Among them, the LSTM model had better results by learning long-term dependencies and trends in stock market data and outperformed the overall performance of ARIMA.

Table 1: Different results in terms of time series prediction.

| Feature | ARIMA Model | RNN/LSTM Models |
|---|---|---|
| Data Type | Linear, stationary data | Non-linear, complex data |
| Model Characteristics | Simple, easy to understand | Complex, harder to understand |
| Prediction Ability | Good for short-term predictions | Good for long-term predictions |
| Data Needs | Small datasets | Requires a lot of data |
| Computational Power | Low computational needs | High computational needs |
| Performance | Good for simple data | Better for complex, volatile data |
| Training Time | Quick to train | Takes longer to train |
| Best Use | Simple forecasting tasks | Complex forecasting tasks |
| Limitations | Struggles with complex data | Can overfit, requires more resources |

## 3.2 Discussion

The study reveals the strengths and limitations of using the ARIMA and the neural network models. ARIMA is recommended for tasks where high interpretability is important, and where the data is linear and stationary since it can be deployed quickly and implemented with low computational power. However, it falters when it comes to non-linear data and conditions that are characterized by sudden changes in trends. However, when it comes to non-linear and non-stationary datasets, the performance of the RNN and LSTM models are found to be significantly better due to their capability of learning from the long-term dependency. Although, these models offer better data estimations especially on the volatile data such as stock prices, they possess higher computational complexities and need large data sets for training. However, training these neural networks takes time; therefore, they are not very suitable for projects that have limited data or computing power.

Future work can explore the integration of the ease of use of ARIMA model with the powerful forecasting performance of RNN and LSTM. Such a combination might prove a more effective compromise between the interpretability of ARIMA and the higher accuracy of neural networks. However, if training becomes less time-consuming and requires fewer data for deep learning models, it expands their application and usability in forecasting.

# 4 CONCLUSIONS

The results presented here prove some advantages and drawbacks of the ARIMA models and the neural network-based solutions. ARIMA is relatively simple to implement and maintain given its high interpretability; it is better suited for linear and stationary data and provides a fast solution that does not consume considerable computational power. Nevertheless, they do not effectively handle non-linear data and sharp changes of trends, which gives them less potential in complex forecast assignments. However, RNN and LSTM models perform very well with quantitative data sets that display non-linear features, including cryptocurrency data that are more inclined to specific time sequences. These models are very proficient in capturing long term trends and tend to exhibit higher accuracy for highly oscillatory data, such as stock price data. However, RNNs and LSTMs have significant computational needs and an extensive amount of training data which can be an issue for a small-scale project or when a large amount of data is unavailable. Another potential area for further research might lie in combining ARIMA with the advantages of RNNs or LSTMs while keeping ARIMA's interpretability in mind. This may provide a balanced solution by refining the ARIMA's forecasting capability and at the same time keeping it simple. Moreover, improvements in the training itself as well as handling of the data could bring the deep learning models to a wider range of applications for forecasting.

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