

**TIME SERIES ANALYSIS FOR MODELING AND PREDICTING  
CONFIRMED CASES OF INFLUENZA A IN ALGERIA**

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**АНАЛИЗ ВРЕМЕННЫХ РЯДОВ ДЛЯ МОДЕЛИРОВАНИЯ И  
ПРОГНОЗИРОВАНИЯ ПОДТВЕРЖДЕННЫХ СЛУЧАЕВ ГРИППА  
А В АЛЖИРЕ**

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## **Abstract**

Influenza A is a subtype of the influenza virus that primarily infects birds and mammals, causing respiratory illness. It is characterized by its ability to mutate rapidly, leading to various strains and occasional pandemics.

**Objective:** This paper is dedicated to studying the distribution behavior and predicting confirmed cases of Influenza A within the Algerian context, a highly infectious disease that causes widespread illness and deaths both in Algeria and globally.

**Methods:** To predict confirmed cases of Influenza A, we implemented several statistical models, including ARIMA, Seasonal ARIMA (SARIMA), ETS, BATS, and the machine learning technique RNN, which is widely recognized in the literature. We then conducted a comparative study using performance measures to evaluate these models.

**Results:** We used RMSE to determine the best-performing model. Our findings indicate that RNN outperformed the others due to its ability to handle complex patterns, including seasonal components and memory. SARIMA and BATS also performed well, thanks to their capacity to manage seasonal patterns. In contrast, ARIMA and ETS showed the poorest performance.

**Conclusion:** This study employed a comprehensive approach to develop a model for predicting confirmed cases of Influenza A in Algeria. The results enhance our understanding of the potential future behavior of this disease and contribute to effective risk management strategies.

**Keywords:** Influenza A, Prediction, Risk management, Time series, BATS, Algeria.

## Резюме

Грипп А является подтипом вируса гриппа, который в первую очередь поражает птиц и млекопитающих, вызывая респираторные заболевания, и характеризуется способностью быстро мутировать, что приводит к появлению различных штаммов и периодическим пандемиям.

Цель: настоящая статья посвящена изучению в Алжире рисунка распространения и прогнозированию подтвержденных случаев гриппа А, высокоинфекционного заболевания, которое вызывает широко распространенные заболевания и смертность как в Алжире, так и во всем мире.

Методы: для прогнозирования подтвержденных случаев гриппа А были применены несколько статистических моделей, включая ARIMA, Seasonal ARIMA (SARIMA), ETS, BATS и широко признанный метод машинного обучения RNN. Далее, мы провели сравнительное исследование с использованием показателей производительности для оценки указанных моделей.

Результаты: для определения наиболее эффективной модели проводилась оценка среднеквадратической ошибки. Наши результаты показывают, что RNN превзошел другие модели благодаря своей способности обрабатывать сложные шаблоны, включая сезонные компоненты и наличие памяти. SARIMA и BATS также показали хорошие результаты благодаря своей способности управлять сезонными закономерностями. Напротив, ARIMA и ETS показали самые плохие результаты.

Вывод: в приводимом исследовании использовался комплексный подход для разработки модели прогнозирования подтвержденных случаев гриппа А в Алжире. Полученные результаты расширяют наше понимание потенциального будущего распространения данного заболевания и способствуют эффективным стратегиям управления рисками.

**Ключевые слова:** грипп А, прогнозирование, управление рисками, временные ряды, ВАТS, Алжир.

1 **Introduction**

2 Influenza A is a viral infection that affects the respiratory system. It is  
3 one of the four types of influenza viruses and can cause symptoms such as  
4 cough, body aches, and sore throat. Highly contagious, Influenza A spreads  
5 through tiny droplets of bodily fluid released during coughing, sneezing, or  
6 talking. Symptoms often include fever, chills, fatigue, and other related  
7 discomforts.

8 In the early 20th century, scientific knowledge was advanced enough to  
9 predict the recurrence of influenza, which had twice reached pandemic levels in  
10 the late 19th century. However, it was largely ineffective in mitigating the  
11 devastating impact of the 1918 pandemic. Since then, humanity has made  
12 significant strides against the disease, developing the capability to design and  
13 produce vaccines and antiviral drugs to prevent or lessen infections.

14 The World Health Organization (WHO) estimates that globally there are  
15 3-5 million cases of severe illness and 290,000-650,000 deaths annually due to  
16 influenza-related respiratory conditions.

17 Nowadays, predicting Influenza A helps minimize the health, economic,  
18 and social impacts of the virus by enabling proactive and well-coordinated  
19 responses. The debate on forecasting Influenza A involves researchers from  
20 various disciplines who use a range of methodologies, including statistical,  
21 machine learning, and deep learning techniques, referencing various studies such  
22 as Goldstein et al.[7], Xu et al.[14], Zheng et al. [16], Kandula et al. [8], Khan et  
23 al. [9], Cheng et al. [4], Wolk et al. [13], Xue et al. [15], Boostani et al. [3],  
24 Al-Qaness et al. [2], Seba et al. [12].

25 This topic has been treated in the Algerian context by several works such  
26 as [6] and [11].The objective of our work is to predict the behavior of new  
27 cases in Algeria using time series analysis. We employ two widely recognized  
28 approaches from the literature: statistical methods and machine learning  
29 techniques for time series analysis.

## 30 **1 Methods and Materials**

### 31 **Descriptive Data**

32 The epidemiology of seasonal influenza is well defined in many parts of the  
33 world, especially in developed countries. However, in other regions, much less is  
34 known about the epidemiology of Influenza A, notably in Algeria.

35 We collect data from: Our world in data-Influenza. We observed that  
36 Influenza A exhibits a seasonal winter pattern because the cold, dry air of  
37 winter provides ideal conditions for the virus's prolonged survival. The  
38 reduced humidity during this season enhances the likelihood of infection. The  
39 significant decrease in Influenza cases from

40 2020 to 2022 can be attributed to several factors related to the COVID-19  
41 pandemic: Implementing public health strategies, including mask wearing, hand  
42 hygiene, social distancing, and lockdowns on a large scale, substantially decreased  
43 the spread of respiratory infections, including Influenza A.

44 Changes in individuals' awareness of safety amid the COVID-19  
45 outbreak.

46 Analyzing monthly-confirmed cases involves treating the data as a time  
47 series. Through- out the literature, various approaches, such as statistical and  
48 machine learning methods, have commonly been employed.

49 Changes in the individual's awareness of safety amid the COVID-19  
50 outbreak. See ([10]). Analyzing monthly confirmed cases involves treating the  
51 data as a time series. Throughout the literature, various approaches such as  
52 statistical, machine learning methods have commonly been employed.

#### 53 **1.1 Preprocessing data analysis**

54 Our data does not contain any missing values but contains seasonal  
55 patterns.

56 We employ the Augmented Dickey-Fuller (ADF) test to assess the  
57 stationarity of the present time series. A p-value of 0.01, which is smaller than

58 the significance level of 0.05, indicates  
59 that the time series is stationary.

60 For data to be considered stationary, the statistical characteristics of the  
61 system must remain constant over time. This does not mean that the values of  
62 each data point must be identical; rather, the overall behavior of the data  
63 should remain consistent.

64 We introduce the Partial Autocorrelation Function (PACF) and the  
65 Autocorrelation Function (ACF) to measure the memory of the most effective  
66 model From the ACF and

67 PACF plots, we observe that the autocorrelation decays exponentially,  
68 indicating that the data has short memory. Additionally, we note the presence  
69 of seasonal components.

## 70 **1.2 Methodology**

71 Various time series analysis models and techniques are employed to  
72 determine the most efficient method for handling validated cases of Influenza A,  
73 utilizing both statistical and machine learning models.

74 We take our data as a time series and split it into two separate sets: the  
75 training set and the test set. The test set, comprising 15% of the data, is used  
76 to validate the best model, while the training set consists of the remaining  
77 85%. We

78 evaluate a model's performance using the Root Mean Square Error (RMSE).

$$79 \quad \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - z_i)^2}$$

80 (1)

## 81 **2 Results**

### 82 **2.1 Predictive models**

#### 83 **ARIMA and ARFIMA model**



84 Autoregressive integrated moving average (ARIMA) models predict  
 85 future values based on past values, it gauges the strength of one dependent  
 86 variable relative to other changing variables.

87 A stochastic process  $(X_t)_{t \geq 0}$  is said to be an ARIMA( $p, d, q$ ) an integrated  
 88 mixture autoregressive moving average model if it satisfies the following  
 89 equation

$$90 \quad \phi(L)(1 - L)^d X_t = \theta(L)\varepsilon_t \quad \forall t \geq \quad (2) \text{Where } d$$

$$91 \quad \in \mathbb{N}, L \text{ is lag operator, } \varepsilon_t \sim \mathcal{N}(0, \sigma^2) \text{ i.i.d. errors, with } \sigma_\infty^2 < \quad .$$

$$92 \quad \phi(L) = (1 - \phi_1 L - \dots - \phi_p L^p) \text{ with } \phi_p = 0$$

$$93 \quad \theta(L) = (1 - \theta_1 L - \dots - \theta_q L^q) \text{ with } \theta_q = 0$$

94 Seasonal ARIMA, is an extension of ARIMA that explicitly supports  
 95 univariate timeseries data with a seasonal component.

96 There are four seasonal elements that are not part of ARIMA that  
 97 must be configured; they are: P: Seasonal autoregressive order, D: Seasonal  
 98 difference order, Q: Seasonal moving average order, m: The number of time  
 99 steps for a single seasonal period SARIMA( $p, d, q$ )( $P, D, Q$ ) $m$

$$100 \quad \phi'(L)\phi(L)(1 - L^m)^d(1 - L)^d X_t = \theta'(L)\theta(L)\varepsilon_t \quad \forall t \geq 0 \quad (3)$$

101 **ETS model**

102 The ETS models are time series models with an underlying state space  
 103 model consisting of a level component, a trend component (T), a seasonal  
 104 component (S), and an error term (E). This method produces forecasts that are  
 105 weighted averages of past observations where the weights of older  
 106 observations exponentially decrease.

107 **BATS model**

108 The BATS (Exponential smoothing state space model with Box-Cox  
 109 transformation, ARMA errors, Trend and Seasonal components) model is a  
 110 time series forecasting model

111 that was proposed by De Livera et al. [5].

112 Box-Cox Transformation component is used to transform the data to  
113 achieve normality and stabilize the variance. The ARMA (Autoregressive  
114 Moving Average) Errors component is used to model the residuals of the  
115 time series data, which are assumed to be independent and identically  
116 distributed. Finally, the Seasonal component is used to model the seasonal  
117 patterns in the data.

## 118 **Recurrent Neural Network RNN model**

119 A Recurrent Neural Network (RNN) model for regression is a type of  
120 neural network designed to process sequential data by maintaining a memory  
121 of previous inputs.

122 Sequential Data Handling: RNNs are ideal for tasks where data points  
123 are dependent on previous ones, due to their ability to maintain information  
124 over sequences.

125 Memory: RNNs have internal memory (hidden states) that captures  
126 information from previous time steps, allowing them to learn patterns and  
127 dependencies over time.

128 Structure: An RNN consists of layers of neurons where each neuron  
129 receives inputs not only from the current time step but also from its own  
130 previous output.

131 Backpropagation Through Time (BPTT): The training of RNNs  
132 involves a variation of backpropagation (BPTT), which updates weights by  
133 considering the entire sequence of data.

## 134 **2.2 Empirical Results**

135 Here, we illustrate the predicted results graphically using several models”  
136 Statistical and machine learning models”.

137 We show numerical results using this measure such as RMSE, A smaller  
138 RMSE and MAE indicates better performance.

139

### 3 Discussion

140 We have applied statistical models: ARIMA, SARIMA, BATS, and  
141 ETS, as well as a machine learning model, RNN.

142 ARIMA is not suitable for modeling and predicting this data due to the  
143 lack of seasonal patterns. Therefore, we opted for SARIMA, which can handle  
144 seasonal patterns. SARIMA performed well in forecasting the confirmed cases  
145 in winter 2023 but exhibit poor performance for the winter of 2024 due to its  
146 short persistence.

147 ETS had the worst performance. We applied simple exponential smoothing  
148 but could not use multiplicative errors and seasonal components due to negative  
149 values. Similarly, the additive case also resulted in negative values.

150 BATS performed well due to its ability to handle seasonal components  
151 and its treatment of errors as ARMA, meaning they are autocorrelated  
152 (dependent), which is more realistic compared to the independent errors  
153 assumed by ARIMA and SARIMA. To improve the results, we replaced  
154 negative values with zeroes.

155 The RNN model performed the best due to its capacity to handle complex  
156 patterns, including nonlinear and periodic trends, and its ability to overcome the  
157 problem of memory. However, it had problems modeling the rest of the year  
158 except for the wintertime.

### 159 **Suggestions for reducing the number of confirmed cases of** 160 **Influenza A**

161 A combination of public health initiatives, personal efforts, and  
162 preventative measures are needed to decrease the number of confirmed cases  
163 of influenza A. The following are some crucial procedures:

164 **Vaccination:** Boost the use of yearly influenza vaccinations, which  
165 aim to protect people against the most prevalent strains that emerge each  
166 season.

167           **Public Health Campaigns:** Organize awareness programs to inform  
168 people about the value of immunizations, good hand cleanliness, and proper  
169 respiratory protocol.

170           **Social Distancing:** Take steps to avoid close proximity in crowded  
171 regions, particularly during the prime time of the flu season. This can involve  
172 advising people to stay away from crowded places, work from home, and keep  
173 a safe distance from other people.

174           **Surveillance and Early Detection:** Implement robust surveillance  
175 systems to: Monitor Influenza Activity: Track the spread and evolution of  
176 influenza strains in real-time. Identify Outbreaks: Quickly detect and respond  
177 to outbreaks to contain their spread.

178           **Data Sharing:** Collaborate with international health organizations for data  
179 sharing and coordinated response efforts.

## 180           **4 Conclusion**

181           To summarize, this work examined the behavior of confirmed Influenza A  
182 cases in Algeria and applied various statistical and machine learning models to  
183 predict the future behavior of this phenomenon. This approach enhances our  
184 understanding of the disease's future trends. Based on our findings, we have  
185 suggested recommendations to help reduce the number of confirmed Influenza A  
186 cases.

## 187           **Acknowledgement**

188           We acknowledge the support of "Direction Générale de la Recherche  
189 Scientifique et du Développement Technologique DGRSDT".MESRS  
190 ALGERIA.

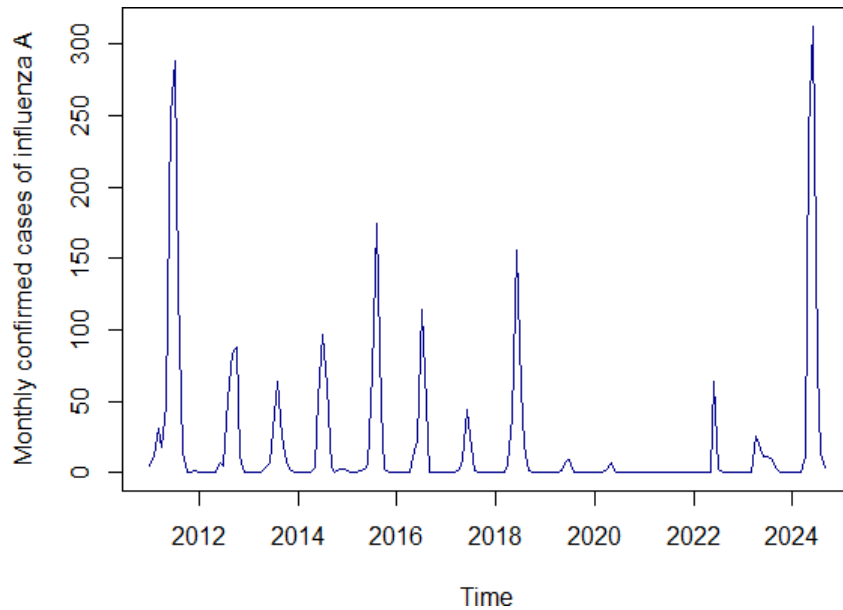
## ТАБЛИЦЫ

**Table 1.** Measure of performance.

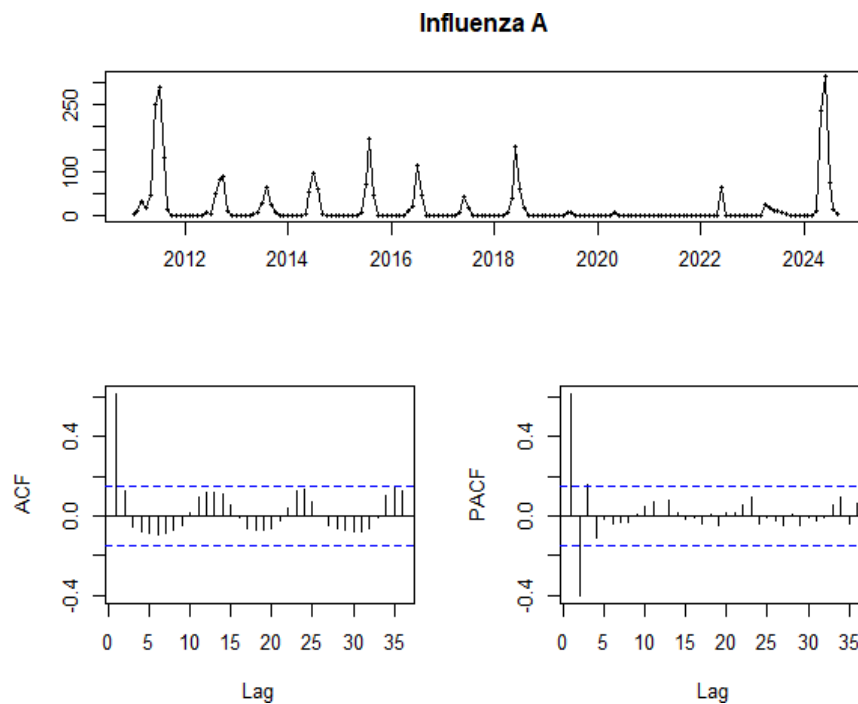
<i>Model</i>	<i>ARIM</i>	<i>SARIM</i>	<i>ETS</i>	<i>BAT</i>	<i>RNN</i>
<i>s</i>	<i>A</i>	<i>A</i>		<i>S</i>	
<i>RMS</i>	78.319	75.176	80.35	74.08	71.33
<i>E</i>			3	8	5

## РИСУНКИ

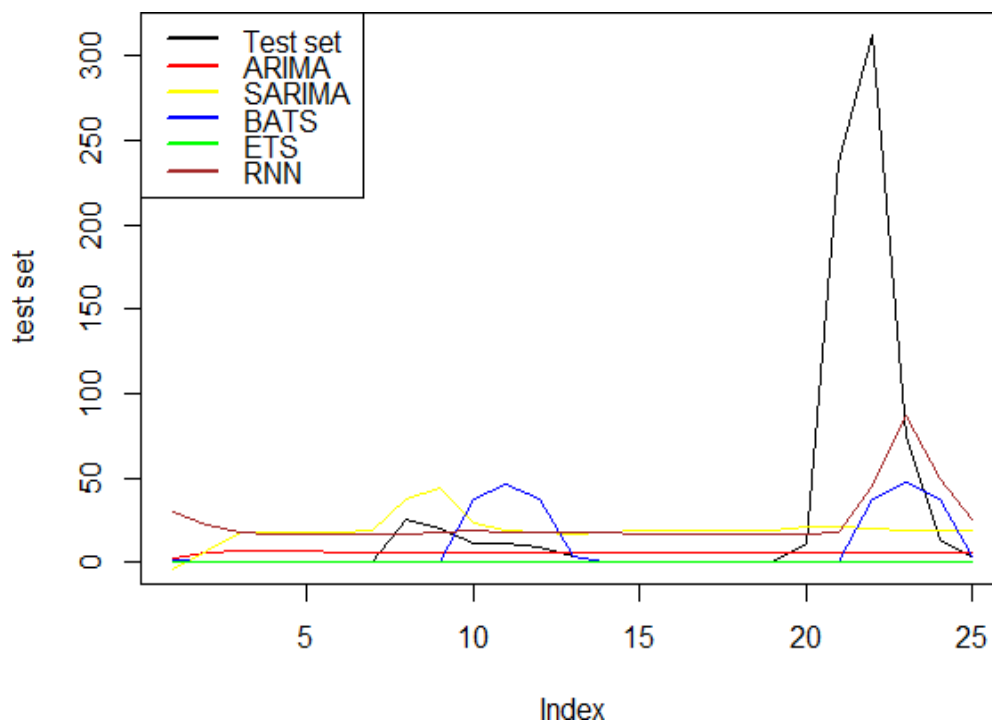
**Figure 1.** Monthly confirmed cases of influenza A.



**Figure 2.** ACF and PACF plots.



**Figure 3.** Predicting confirmed cases of Influenza A in Algeria.



## ТИТУЛЬНЫЙ ЛИСТ\_МЕТАДААННЫЕ

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**Блок 3. Метаданные статьи**

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Оригинальные статьи.

Количество страниц текста – 8,

количество таблиц – 1,

количество рисунков – 3.

14.06.2024

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