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CONSIDERATIONS ON THE EFFICIENCY OF TIME SERIES ANALYSIS IN FORECASTING NEW INFLUENZA CASES IN THE 2024-2025 SEASON

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ABSTRACT

A subject of high interest in epidemiology is to register monthly and yearly the prevalence of certain diseases, in order to make prognosis regarding the expected number of new patients. The best way to solve such problems is provided by the Time Series Analysis technique, which is a statistical modelling method able to make forecasts. We discuss about the theoretical bases of this method and we exemplify its practical applications in making forecasts about the expected number of Influenza cases in Romania, during a period of 11 weeks (March – May 2025) based on weekly records about Influenza during the last two seasons (2023-2024 and 2024-2025). The forecasts were made in SPSS 29.0, using the Expert Modeler module, and the best suitable models found were Simple Seasonal and ARIMA(0,1,0)(0,0,0). The paper presents the results of this analysis and the predicted values, with 95% confidence intervals.

Keywords: time series analysis, forecasting, Influenza

INTRODUCTION

Statistical forecasting is an essential tool of data analysis, with extended applicability in different domains, medical sciences being included. This sort of analysis aims to describe a system's behaviour through the dynamics of its components, allowing therefore to detect trends and to anticipate future evolutions [1]. To reach its goals, it applies mathematical analytic tools on historical data and estimates the phenomenon's future evolution, allowing therefore to take informed decisions in conditions of uncertainty. In medicine the statistical forecasting plays a key role in anticipating the diseases' evolution and the treatments' efficacy, being widely used in epidemiology, but also in medical management and even in clinical studies.

There are multiple techniques of forecasting, which depends mainly on the involved data nature and the study's purposes. A first attempt of classification identifies four main types of statistical prognoses: the deterministic prognoses, which uses fixed mathematical models in order to make accurate estimations; the probabilistic prognoses, based on probabilities distributions and estimations of the uncertainty; short term and long term prognoses, related to the time referred, and univariate and multivariate prognoses (the univariate models use a singular variable for estimation, while the multivariate models take into account multiple factors which influence the studied phenomenon).

There are also different calculation methods available to perform the statistical prognoses. The simplest approach is represented by the regression models (the linear and logistic models being the most popular); such models allow to highlight the relations between variables and to estimate risks and trends in medical studies. Another approach is represented by the Time Series Analysis; first published in the late of 1950s and applied in econometric studies, the techniques included here (like the ARIMA models or the methods of Exponential Smoothing) were quickly recognized as strong

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and useful tools in the analysis of periodical data, with good applications in fields like psychology, psychometrics, sociology and epidemiology [2]. Other approaches, newer but more and more popular, are represented by the Markov models, recommended in the analysis of stochastic processes, like the progression of chronical diseases and, finally, by the Machine Learning techniques, based on neural networks, able to create complex prognoses in medicine [3,4].

Statistical forecasting plays an essential role in the evidence-based medicine, because it provides valuable information for diseases prevention, diagnosis and treatment. For example, it allows to anticipate the chronic diseases evolution (like diabetes, cardiovascular disease or cancer), eventually in relation with certain risk factors like age, lifestyle and medical history. It is also essential in epidemiology, to anticipate and control the spread of infectious diseases; the SEIR models (Susceptible – Exposed – Infected – Recovered), for example, allow to estimate the epidemic and pandemic spread (like COVID-19) and sustain the decisions regarding the quarantine, vaccination plan and allocation of medical resources [5]. The statistical forecasts are also involved in evaluation of the medical treatments' efficiency and safety, in which concerns the risk of secondary effects, the chances of full recovery or the impact of different drugs on certain diseases. Such information is also highly significant for the personalized medicine approaches – the Machine Learning techniques and the statistical models can help to adapt the treatment plan to the patients' genetic and clinical data and to design customized prevention strategies [6]. Finally, but not at least, the statistical forecasts can optimize the medical resources management by evaluating the demand of hospital beds, medical devices or even medical staff.

There are also challenges and limits. The utility of statistical forecasting is highly sensitive to the quality and accuracy of the raw data – missing or wrong data leading easily to wrong prognoses; the models based on specific samples are not always applicable to other medical populations and they don't address always all the relevant variables, taking in consideration the fact that the biological systems are always extremely complex and random in their behaviour.

Despite these difficulties, the role of forecasting in nowadays medicine is undeniable, not only in improving patient outcomes, but in enhancing the whole public health planning. One of its most important beneficiaries is represented by epidemiology, where predictive models are able to track the infectious diseases trends, to highlight potential outbreaks and to facilitate proactive mitigation measures.

Our paper addresses this particular topic. One of the main areas of interest in epidemiology is to survey the epidemic diseases behaviour by recording the daily number of cases, in order to evaluate the virulence and severity of the disease and to design well-tailored strategies of control and treatment. Since such data are clearly time related, being usually periodically and sometimes seasonal, the statistical forecasting through Time Series Analysis is highly suitable to make valid prognosis regarding the expected number of new patients [7]. The difficulty consists instead in finding the best model, able to provide the most accurate forecasts. We approached this issue on theoretical as well as on practical bases, starting from a specific and rather common problem: making realistic forecasts about the expected number of Influenza cases in Romania, in a period of 5 weeks (March – April 2025) based on weekly records about Influenza's incidence during the last two seasons (2023-2024 and 2024-2025).

MATERIAL and METHODS

A. Theoretical background

Time Series Analysis is a method of forecasting designed for data obtained through measurements which follow a deterministic order, being usually made at equal time intervals; such measurements illustrate the dynamic in time of a certain process, being also called "dynamic series" [8, 9]. The Time Series Analysis main purpose is to predict the future values in a time series based on previously

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reported data; such predictions are based on the time series pattern, properly identified and formally described.

A time series, or a dynamic series, is usually denoted by (ξ_t, t $\in$ T), where T$\subseteq$ **R** represents the time. The data ξ_t are usually recorded periodically (weekly, monthly, seasonally), even if there are also models for time data recorded continuously. Among the dynamic models based on time series, the most important are the adjustment models, the auto predictive models and the explicative models [9].

The adjustment models are described through the equation:

$\xi_t = f(t, u_t)$, where
f = function which contains a finite number of unknown parameters,
u_t = random variable with average 0 which describes a real situation.

The auto predictive models are described through the equation:

$\xi_t = f(\xi_{t-1}, \xi_{t-2}, \ldots, u_t)$, where
u_t = random variable which represents a disturbance factor.

The explicative models are described through the equation:

$\xi_t = f(x_t, u_t)$, where
x_t = also called exogenous variable, is an observable variable,
u_t = random variable which represents a disturbance factor.

The explicative models can be also divided in two categories: static, where x_t doesn't contain information regarding the past values of ξ_t and u_t are mutually independent; and dynamic, where x_t contains contain information regarding the past values of ξ_t or u_t are auto-correlated.

There are four main components of a time series [8]:

- the trend, which represents the long-term movement or directionality of the data over time. It captures the overall tendency of the series to increase, decrease, or remain stable. Trends can be linear, indicating a consistent increase or decrease, or nonlinear, showing more complex patterns; trend changes in time and does not repeat itself;
- the seasonality, which refers to periodic fluctuations or patterns that occur at regular intervals within the time series;
- the cyclic variations – are longer-term fluctuations in the time series, without a fixed period like seasonality; they can extend over multiple years and are usually associated with external factors;
- the irregularity (or noise) – it refers to the data random fluctuations that cannot be attributed to the trend, seasonality, or cyclic variations; it can be caused by random events, measurement errors, or other unforeseen factors and hides the time series underlying patterns, making it challenging to identify.

The time series analysis' main task is to remove the noise, in order to highlight its pattern [8]; the technical solution is to smooth the time series using moving averages: simple (SMA, $SMA(\xi_t) = \frac{(\xi_t + \xi_{t-1} + \ldots + \xi_{t-n+1})}{n}$); weighted (WMA, $WMA(\xi_t) = \frac{(n \cdot \xi_t + (n-1) \cdot \xi_{t-1} + \ldots + 2 \cdot \xi_{t-n+2} + \xi_{t-n+1})}{n + (n-1) + \ldots + 2 + 1}$); exponential or exponentially weighted, where ξ_t is a given value in a time series and n are previous values of ξ_t.

The pattern of a time series is identified through specific decomposition techniques, as it follows: autocorrelation analysis (measures the correlation between a time series and a lagged version of itself, helping to identify patterns and data dependencies); trend and seasonality analysis; or spectrum analysis (investigates the frequency domain representation of a time series to identify dominant frequencies or periodicities, which usually correspond to cyclic patterns).

The scientific literature reported different algorithms with good results in time series forecasting [10]. A first category is represented by the Autoregressive Models (AR), that predict future values based on linear

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combinations of past values of the same time series plus a random error term; the order of the autoregressive model (p) shows how many past values are used in the prediction [11]. One of the best models used in forecasts is ARIMA (Autoregressive Integrated Moving Average), developed by Box and Jenkins in 1976; it is widely used and models the future value in a time series based on linear combinations of past values plus past forecast errors [12]; the model is therefore characterized by 3 parameters, p (the order of autoregression), d (the gap of differentiated transformation) and q (the moving average parameter). Other extensions of ARIMA are ARIMAX (which includes exogenous variables to improve accuracy) or SARIMA (which incorporates the seasonality). The Vector Autoregression (VAR) models extend autoregression to multivariate time series data by modeling each variable as a linear combination of its past values and the past values of other variables and forecasting interdependencies among multiple time series. The Theta models make forecasts based on extrapolation and trend fitting. The Exponential Smoothing models, proposed by Brown, Holt and Winters in the late 1950s, use weighted averages of past observations, with the weights decaying exponentially as the observations get older; these methods are particularly useful for data with trend and seasonality; among them, special approaches are represented by Simple Exponential Smoothing (SES) models – which actually corresponds to an ARIMA (0,1,1), with no constant and a smoothing parameter called level, and Simple Seasonal Exponential Smoothing (SSES) model, characterized through level and season parameters.

The Gaussian Processes Regression is a Bayesian non-parametric approach that models the distribution of functions over time, allowing to capture uncertainty in time series forecasting. The Generalized Additive Models (GAM) combine additive components, suitable to model nonlinear relationships and interactions [13]. The State Space models represent the time series as combinations of unobserved (hidden) states and observed measurements; in this way they become able to capture both the deterministic and stochastic components and to detect the possible anomalies [14]. The Dynamic Linear Models (DLMs) are Bayesian state-space models that represent time series data as a combination of latent state variables and observations, being able to reveal dynamic patterns in data [15]. The Hidden Markov Models (HMM) describe sequences of observable events generated by underlying hidden states, capturing dependencies and transitions between states [16].

One last category contains the models based on Machine Learning techniques. Some relevant examples in this regard are: the Recurrent Neural Networks (RNNs) [17] and Long Short-Term Memory (LSTM) Networks [18, 19], which are deep learning architectures designed to handle sequential data, able to capture complex temporal dependencies in time series data; the Random Forest models, that build multiple decision trees during training and output the average prediction of the individual trees, being able to handle complex relationships and data interactions [20], as well as the Gradient Boosting Machines (GBM), that build multiple decision trees sequentially, where each tree corrects the errors of the previous one, robust against overfitting and being able to capture nonlinear relationships [21, 22].

B. Practical framework

In order to investigate the current and future evolution of Influenza cases, we used the public reports made by INSP (National Institute of Public Health, www.insp.ro), regarding the weekly cases recorded in Romania during the last 2 seasons (2023-2024 and 2024-2025). According to the official reports, the Influenza season usually lasts around 33 weeks, between October 1st (the 40th week of the year) and May 20th (the 20th week of the next year). We took into account all the reports from the season 2023-2024, and the reports from the first 22 weeks of the season 2024-2025, in order to forecast the number of cases for the rest of the 2024-2025 season (the weeks 23-33). We focused our analysis on the total number of Influenza cases, as well as,

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separately, on the number of Influenza A Type, Influenza B Type and the number of deaths.

The data were processed in SPSS 29.0, using the Expert Modeler module for Time Series Analysis; this module has the advantage to check all the available algorithms of temporal modelling and to select the model which makes the most accurate prognosis.

RESULTS

In the first step of our analysis, we checked the time series in order to detect if they have or not any seasonal components (it was reasonable to assume that there are good chances to detect a seasonal component, because the Influenza cases are strongly correlated with the cold weather and the winter season). The easiest way to detect the seasonal components is by performing Sequence Charts – these are charts which represent the evolution of cases in time. The presence of periodic peaks on the charts (for Influenza A Type, the total number of Influenza cases as well as for the number of deaths) revealed a certain component of seasonality (fig. 1-4), which will be necessary to build the final model.

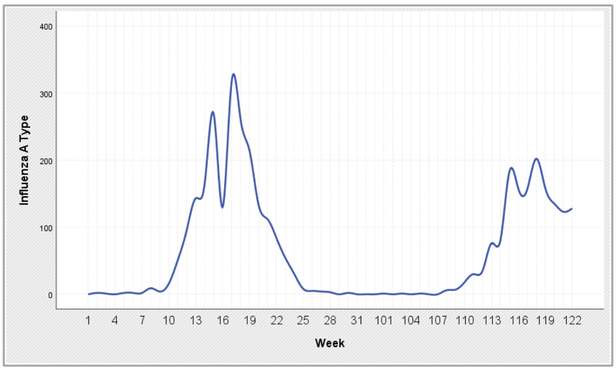

Fig. 1. The Sequence Chart for Influenza A Type number of cases

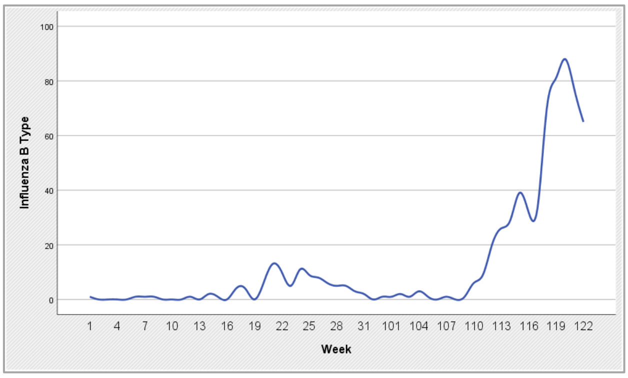

Fig. 2. The Sequence Chart for Influenza B Type number of cases

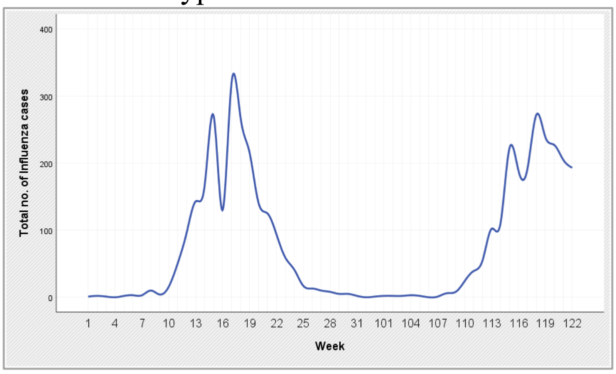

Fig. 3. The Sequence Chart for total number of Influenza cases

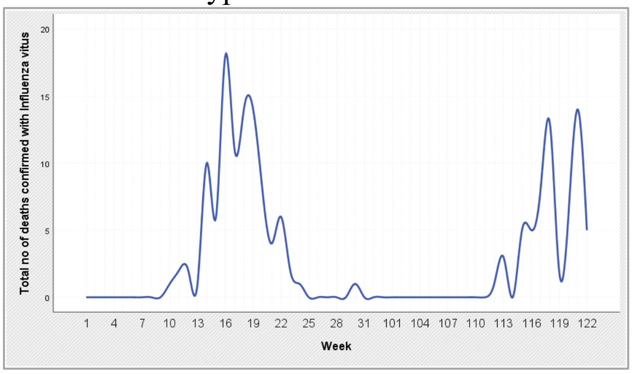

Fig. 4. The Sequence Chart for total number of Influenza deaths

In the next step we performed the autocorrelation analysis, in order to identify potential patterns, trends or lags in the data. We made the ACF plots (necessary to show how are the variables correlated with their past values at different lags) and the PACF plots (necessary to identify direct relationships between variables and their past values). The obtained results are presented in figures 5-8.

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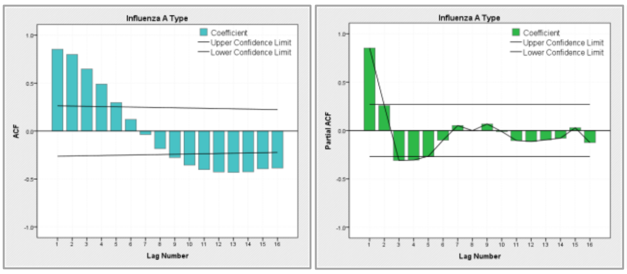

Fig. 5. The ACF and PACF plots for Influenza A Type number of cases

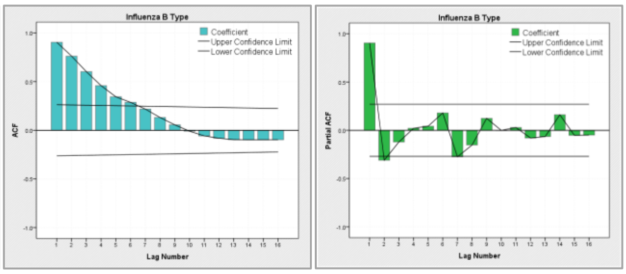

Fig. 6. The ACF and PACF plots for Influenza B Type number of cases

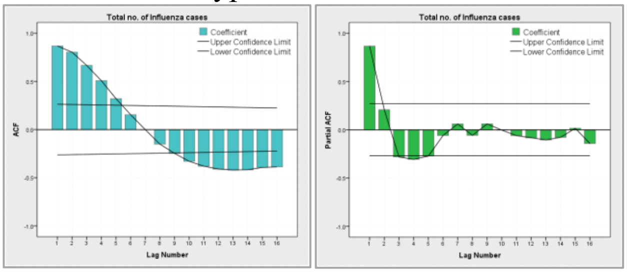

Fig. 7. The ACF and PACF plots for total number of Influenza cases

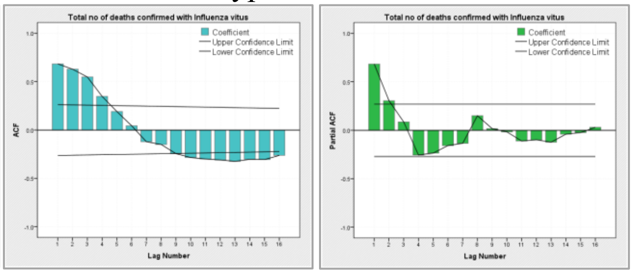

Fig. 8. The ACF and PACF plots for total number of Influenza deaths

In case of Influenza A Type the autocorrelation is significant at the first few lags and then gradually decreases (on ACF chart), showing that the number of cases in a given week has a certain persistence, being correlated with the previous weeks. The significant spike at lag 1 (on PACF chart), followed by a visible decline, shows that the previous week has the most important influence on the current week. Influenza B Type has a similar behaviour, but with a weaker persistence than A Type. The total number of influenza cases has the highest persistence, at the lags 1 and 2 – the number of cases in a given week is correlated with the previous two weeks, and not only with the last one. The number of deaths has lower autocorrelation values, without a clear weekly pattern; this means that flu deaths may be influenced by external factors, and not by the past flu cases alone.

In the last step we performed the Time Series Analysis, using the Expert Modeler module available in SPSS 29.0. The time series were structured on weeks, between October 2023 and March 2025, and we set up the prognosis period at 11 weeks (March – May 2025).

The prediction models generated for our time series were Simple Seasonal for the Influenza A Type, total number of Influenza cases and total number of Influenza deaths, and ARIMA(0,1,0)(0,0,0) for Influenza B Type.

The model statistics (Table 1) show that the selected models fit well the existent data; the R-squared values show the amount of data variance explained by models. The best values were obtained for Influenza B Type (91.8%), followed by the total number of Influenza cases (82.5%) and Influenza A Type (79.3%). Stationary R-squared measures the stationarity explained by the models; the values bigger than 0.5, recorded for Influenza A Type, the total number of Influenza cases and the total number of Influenza deaths, show that the models capture well the trend dynamics. Ljung-Box Q test checks if residuals are white noise; the significance level p over 0.05 suggests that the model residuals are not correlated, which means a good fit (in case of Influenza B Type and the total number of Influenza cases); the other two models may require some improvements. No outliers were detected.

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Table 1. Model Statistics for the Analyzed Time Series

Model	Model Fit statistics		Ljung-Box Q			Number of Outliers
	Stationary R-squared	R-squared	Statistics	DF	Sig.	
Influenza A Type - Model_1	.644	.793	29.880	16	.019*	0
Influenza B Type - Model_2	2.220E-16	.918	10.523	18	.913	0
Total no. of cases - Model_3	.634	.825	27.098	16	.040*	0
Total no of deaths - Model_4	.571	.574	16.696	16	.406	0

The results of the forecast are presented in Table 2 and fig. 9. For each month we calculated the most probable number of cases and its 95% confidence level (UCL – highest expected cases and LCL – lowest expected cases).

Table 2. Forecast values for the Analysed Time Series

Model	Forecast	Week										
		23	24	25	26	27	28	29	30	31	32	33
Influenza A Type	Value	97	91	98	100	131	115	120	149	112	146	133
	UCL	174	190	215	232	277	274	290	330	303	346	343
	LCL	20	-7	-19	-32	-15	-43	-50	-32	-79	-55	-77
Influenza B Type	Value	66	67	69	70	71	72	73	74	76	77	78
	UCL	79	86	91	96	100	104	108	111	115	118	121
	LCL	53	49	46	44	42	40	39	38	37	36	35
Total no. of cases	Value	154	153	160	162	197	177	181	217	182	218	204
	UCL	235	256	282	300	350	343	360	407	382	429	425
	LCL	73	49	38	24	44	11	3	27	-18	8	-16
Total no. of deaths	Value	5	4	6	4	5	4	7	7	7	6	9
	UCL	11	11	14	13	15	15	18	18	19	19	22
	LCL	-1	-3	-3	-5	-5	-6	-4	-5	-5	-6	-4

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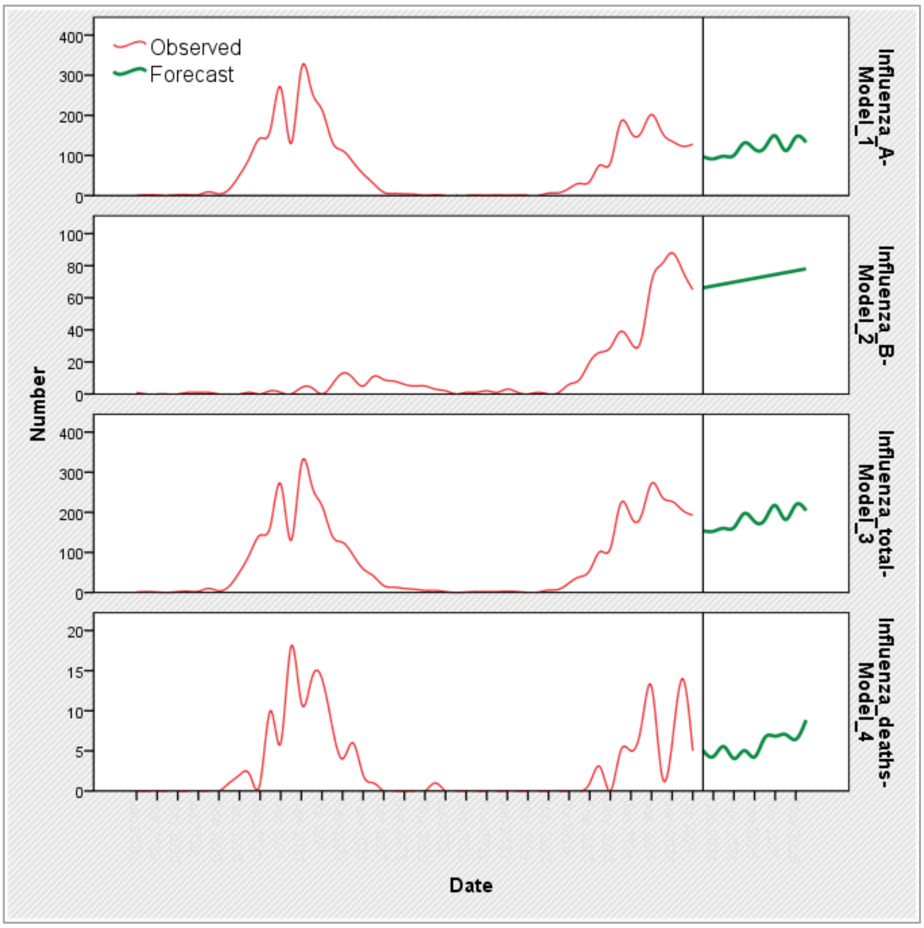

Fig. 9. Forecast values for the Analysed Time Series

In case of Influenza A Type, the forecast cases fluctuate around 90-150 cases per month; the UCL values increase significantly in time, suggesting higher uncertainty in later forecasts, while the LCL negative values suggest possible problems of model overfitting or incorrect variance assumptions. The Influenza B Type model provides more stable predictions compared to Influenza A, with no negative values for LCL and a narrower range of variation; the number of cases is also significantly lower, between 66 and 80. The predictions for Influenza total number of cases are also rather reliable and vary around 150-220 cases per month. The Influenza number of deaths, as expected, is small (at most 9 cases per week), but the rather wide ranges of variation, with negative values for LCL, show certain inaccuracies of the model.

DISCUSSIONS

In this paper we used the Time Series Analysis to obtain forecasts regarding the weekly number of Influenza cases in Romania for the end of the 2024-2025 season. We worked with an automated module, designed to test different time series models (Exponential Smoothing, ARIMA univariated and ARIMA multivariated) and to select the model with the best fitting to data. The identified models were Simple Seasonal and ARIMA(0,1,0)(0,0,0) – reasonable finding since the Influenza epidemic is clearly related to the cold weather, and the historical data reported that Influenza outbreaks exhibit strong seasonal patterns and periodic surges. The models proposed have a good quality, but they are not perfect; possible improvements can address the autocorrelation in residuals and the overfitting. A very useful enhancement in forecast can be also obtained by adding exogenous variables (like temperature, humidity, population mobility or

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vaccination rates), but such data were not available at the moment when our analysis was performed.

The current researches about forecasting propose more complex approaches – like the Kalman filtering, able to perform real-time updating when new data becomes available, the regression-based and hybrid models, which incorporate external variables and improve the predictive accuracy, as well as the Machine Learning techniques (Long Short-Term Memory Networks LSTM, able to reveal long-range dependencies in trends or Bayesian Structural Time Series BSTS, which provide an improved management or prior information and uncertainty) [23]. The advantages of such approaches are undeniable, but there are also significant challenges to be addressed. First of all, reliable forecasts require high-quality data, which are not always available, due to reporting delays or underreporting; secondly, there are external factors, negative (like virus mutations) or positive (well-targeted public health interventions and changes in human behaviour), which can significantly change the disease's dynamics, and thus the prognoses' quality [24].

CONCLUSION

It is obvious that Time Series Analysis provides reliable results in infectious diseases forecasting, valuable for epidemic preparedness and response. Such investigations are mandatory for the specialists in Epidemiology and Public Health, allowing them to get new insights about the outbreaks' scale and spread, and equally to implement efficient measures for anticipation and mitigation, and ultimately for morbidity and mortality improved control. The main challenge in the field is to find the best suitable models, with enhanced accuracy – the solution seems to develop hybrid models, which incorporate complementary techniques, as machine learning or spatial analysis, being therefore able to take into account supplementary data and to analyse accordingly their external influences.

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