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Addressing non-stationarity with stochastic trend in the context of limited time series data: An experimental survey in healthcare analytics

Abstract

Stationarity is a fundamental assumption in time series modeling that underlies reliable statistical inference and forecasting. Time series data can be found in many domains, including industry, engineering, finance, economics, epidemiology, and health care analysis. This study addresses stochastic non-stationarity arising from unit root processes. It explores the efficacy of fractional differentiation as a means of achieving stationarity, especially in the context of limited-sample time series data, and attempts to confirm it statistically through experiments. To this end, 24 series of malaria and typhoid incidence were used, from the Adamawa region of Cameroon, collected weekly from January 2021 to December 2023, 14 of which were non-stationary. Four models were tested: Autoregressive Integrated Moving Average (ARIMA), Fractional ARIMA (ARFIMA), Long Short-Term Memory (LSTM), and a hybrid Fractionally-Differentiated-LSTM (FD-LSTM) proposed in this paper. The accuracy of the prediction models was assessed by the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2) values. The results show that the Pearson correlations between the original time series and the integer-differentiated series are weak, mainly between 0.2 and 0.4, while they are between 0.75 and 0.98 for the fractional-differentiated series. Moreover, ARFIMA outperforms ARIMA by 93% in training and 100% in testing, while FD-LSTM achieves a 100% improvement over the standard LSTM model. These results contribute to the methodological toolkit for time series forecasting in data analytics and highlight the statistical and practical advantages of fractional differencing in small sample preprocessing.

1. INTRODUCTION

1.1. Background

Time series techniques are statistical tools that have long been used in diverse fields such as economics, finance, meteorology, industry, engineering, epidemiology, and healthcare analytics to derive accurate predictions and insights from sequential data over time (Diebold & Rudebusch, 2020; Dudek et al., 2024; Hyndman & Athanasopoulos, 2021; López de Prado, 2018). Although most epidemiological and health care data are collected as time series data, the sophisticated application of time series methods remains underutilized in this field, as demonstrated by Batoure Bamana et al. (2024), Z. Liu et al. (2021), and Sandhya Arora (2024). In addition, unlike sectors such as finance, meteorology, or industry, where data is collected at high frequency intervals (minutes, hours, or days), epidemiological data and records of natural hazards (e.g., floods, famines, earthquakes, or tsunamis) are typically collected at less frequent intervals (weekly, monthly, or even annually), which often limits the amount of data available (AghaKouchak et al., 2022; Fung et al., 2020; Livieris et al., 2021; Nurtas et al., 2024; Sadhukhan et al., 2023; Singh et al., 2024).

Indeed, many real-world time series exhibit non-stationarity, meaning that important properties such as mean, frequency, variance, and kurtosis vary over time (Aieb et al., 2024; Batabyal et al., 2023; Han et al., 2024; Ryan et al., 2025; van Greunen et al., 2014). Given the data limitations in critical areas where lives may be at stake, achieving the accuracy required for reliable statistical inference and prediction is paramount (Batoure Bamana et al., 2025). Without stationarity, many standard statistical procedures can produce biased or inconsistent estimates, undermining the validity of conclusions (Brandão & Nova, 2009; Z. Liu et al., 2021; Livieris et al., 2020). When these properties are stable, analysts can confidently apply statistical tests and forecasting models without the risk of spurious correlations arising from underlying trends or volatility shifts (Ryan et al., 2023; Salles et al., 2019). Moreover, stationary data simplify the modelling process by reducing the complexities associated with trends, seasonality, and heteroskedasticity, thereby facilitating a more straightforward interpretation of results (Diebold & Rudebusch, 2020; Dixit & Jain, 2021; Han et al., 2020).

Stationarity can manifest itself in two forms: deterministic trend, also known as trend stationarity (TS), and stochastic trend or difference stationarity (DS) (Brandão & Nova, 2009; Dudek et al., 2024). Non-stationary time series with stochastic trends are of particular interest in this paper, as they pose challenges for accurate modelling and forecasting. To eliminate no stationarity, the time series is transformed by differentiation, a process that can be implemented using either integer or fractional approaches (Flores-Muñoz et al., 2019; Lahcen, 2023; López de Prado, 2018; Maitra et al., 2023). Therefore, this study investigates how differentiation in preprocessing can improve prediction scores for datasets with limited volume, and evaluates which approach, integer or fractional, is more appropriate based on the findings of this experimental investigation.

1.2. Literature review

Several scientific studies have addressed the challenge of nonstationary time series, focusing primarily on methods to transform these series into stationary forms for further analysis.

Livieris et al. (2021) propose a framework that improves deep learning models for time series analysis by using advanced data preprocessing techniques. Their framework transforms the original low-quality time series data into high-quality data, making it suitable for efficient training and fitting of deep learning models. Dixit and Jain (2021) investigates how time series stationarity affects forecast accuracy and error rates. The paper begins by classifying the datasets with respect to their stationarity properties. Forecasting models are then applied to the datasets and the results indicate that non-stationary datasets have lower accuracy and higher error rates. According to Aieb et al. (2024), forecasting climate variability in non-stationary time series is improved by employing innovative data preprocessing techniques that adjust for non-uniform distributions, streamline time lag detection through autocorrelation, and effectively address non-stationarity challenges. Recently, Han et al. (2024) proposed an innovative model that combines signal decomposition and deep learning techniques to address the challenge of non-stationarity. Their model employs Generalized Autoregressive Conditional Heteroskedasticity (GARCH) to capture volatility changes, followed by Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) for data decomposition. Satyaveer et al. (2023) propose a hybrid model that combines ARFIMA-LSTM and a sentiment analysis model. The authors apply this new model to stock market forecasting.

The remainder of this section discusses techniques for making a time series stationary. Some related work includes K. Liu et al. (2017), which showed that the ARFIMA model has broader applications due to its ability to capture short- and long-run dependencies. Walasek and Gajda (2021) implemented fractional differentiation on four major international stock index datasets and compared fractional and classical differentiation in the context of Artificial Neural Networks (ANN), using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as performance measures. Rabiu Haruna et al. (2024) looked at malaria disease and control in Bauchi State, Nigeria. They used 120 samples collected monthly to fit ARIMA, Seasonal ARIMA (SARIMA), and ARFIMA models according to the best Akaike Information Criterion (AIC). The results show that ARFIMA outperforms both ARIMA and SARIMA models. Other important works use change-point analysis to deal with nonstationarity by segmenting the time series into homogeneous intervals (Shafiee Kamalabad et al., 2019; 2023; Shafiee Kamalabad & Grzegorczyk, 2020). Although this method can isolate segments that are more likely to be stationary, it may oversimplify the underlying data dynamics by neglecting transitional behavior between segments.

Taken together, these studies emphasize the need to achieve stationarity during the preprocessing phase, using integer or fractional differentiation of the time series, before applying a predictive model.

1.3. Contributions of the work

Building on the findings presented in the background and literature review, the present study contributes theoretically and practically in several significant ways:

- A comparative framework that evaluates classical and fractional differentiation approaches, facilitating an objective assessment of their relative merits;
- Principles of nonstationarity, detailing its various types, the statistical tests used to identify them, and the role of differentiation in achieving stationarity;
- Predictive capabilities when data are limited, suggesting potential avenues for further analysis in data-poor environments;
- A structured process for data collection, curation, and classification that creates a robust dataset that can serve as a foundation for subsequent research;
- A novel Fractionally Differentiated LSTM (FD-LSTM) framework to effectively handle non-stationary time series and improve forecasting performance;
- Discuss and interpret the results, providing insights, conclusions, and actionable recommendations relevant to decision makers and researchers, with the potential for generalization to other fields.

The paper is based on actual public health data and addresses real-world challenges using up to 24 series, including 14 non-stationary ones, for experiments. The datasets are limited in terms of recorded observations, in contrast to the larger datasets used in other studies. No such work on stationarity properties has been considered in this geographical area and on these datasets. The added value of this experimental survey on non-stationary time series with stochastic trends lies in its assessment of the impact of differentiation on time series and the degree of forecasting improvement. This experimental study is situated within the data analysis and forecasting framework, specifically applied to epidemiological and healthcare analytics domains, and contributes to advancing statistical methodologies applicable across diverse fields.

2. STATIONARITY IN TIME SERIES

2.1. Types and tests of stationarities

Stationarity refers to a property of a stochastic process in which the unconditional joint probability distribution remains invariant under time shifts (Aieb et al., 2024; Brandão & Nova, 2009; Ryan et al., 2023). This invariance refers to fundamental statistical moments, such as the mean, variance, and kurtosis (Chaudhuri et al., 2018).

The sequence $\{x_t\}$ of random variables is strictly stationary (or stationary of first order) if the joint distribution of $\{x_t\}$ and $\{x_{t+h}\}$, for any t and h, remains the same when shifted in time. Equation (1) formally expresses the notion of first-order stationarity, where f represents the joint distribution function (Batoure Bamana et al., 2024).

$$f(x_t,\dots,x_{(t+h)})=f(x_\tau,\dots,x_{(\tau+h)}),\quad t\neq\tau \tag{1}$$

However, verifying strict stationarity can be difficult in practice. Therefore, second-order stationarity is often introduced as a more tractable alternative (Livieris et al., 2021; Sadhukhan et al., 2023). A random process $\{x_t\}$ is second-order stationarity when:

- Its mean and variance are independent of time and finite:

$$\begin{cases} \forall t, E(x_t) = \mu < \infty \; and \; E(x_t^2) = \mu_2' < \infty \\ \forall t, Var(x_t) = \mu_2'^2 - \mu^2 = \gamma_0 < \infty \end{cases} \tag{2}$$

- The covariance between two times separated by an interval τ is finite and depends only on τ:

$$\forall t, Cov(x_t + x_{t+\tau}) = E(x_t + x_{t+\tau}) - \mu^2 = \Upsilon_\tau < \infty \tag{3}$$

If either of these conditions is not met, the series is non-stationary. Therefore, a time series can exhibit the two primary forms of non-stationarity: trend stationarity (TS) and difference stationarity (DS). One form of nonstationarity does not necessarily imply the other (Afriyie et al., 2020; Brandão & Nova, 2009).

Trend stationarity (TS) characterizes time series processes in which the variance remains constant over time while the mean exhibits a deterministic trend, typically increasing or decreasing systematically. This process is therefore of the form $E(x_t) = \alpha + \beta t, Var(x_t) = \sigma^2$and is said to have a deterministic tendency, expressed as

$$\begin{cases} x_t = \alpha + \beta t + \mu_t \\ \Phi(L)\mu_t = \theta(L)\varepsilon_t \\ \varepsilon_t \sim iid(0, \sigma_\varepsilon^2) \end{cases} \tag{4}$$

where α and $\beta$are constant coefficients, $L$is the lag operator, $\Phi(L)$and $\theta(L)$satisfy stationarity conditions, and $\varepsilon_t$is the error of the model at time t. The process is nonstationary because the mean $E(x_t) = \alpha + \beta t$depends on time t.

In difference stationarity (DS), the time series is stationary in its mean but not in its variance. Equation (5) below defines the DS process:

$$\begin{cases} x_t = x_{t-1} + \beta + \varepsilon_t \ ie \ (1 - L)y_t = \beta + \mu_t \\ \Phi(L)\mu_t = \theta(L)\varepsilon_t \\ \varepsilon_t \sim iid(0, \sigma_\varepsilon^2) \end{cases} \tag{5}$$

The variables in equation (5) are the same as in equation (4). There are two typical cases, depending on whether β is zero or not:

- $\beta = 0$: The process is stochastic, written as $x_t = x_{t-1} + \varepsilon_t$, and known as a driftless random walk process.
- $\beta \neq 0$: The process is a random walk with drift. It thus exhibits non-stationarity with a stochastic nature of the form $x_t = x_{t-1} + \beta + \varepsilon_t$.

A time series with difference-type nonstationarity can be viewed as a random walk (with or without drift) and is said to have a unit root, indicating a stochastic trend. To make such a series stationary, it must be differentiated $d$time. Accordingly, a series that requires d. Differencing operations is described as integrated of order d. When d is a nonzero integer, the differencing is complete; otherwise, it is fractional, indicating fractional differencing (Maitra et al., 2023; Salles et al., 2019; Wang et al., 2023).

There are several approaches to testing the stationarity of a time series, each tailored to assess specific aspects of stationarity. Commonly used tests include the Dickey-Fuller (DF) (Leybourne et al, 2005), Augmented Dickey-Fuller (ADF) (Mushtaq, 2011; Paparoditis & Politis, 2018), Phillips and Perron (PP) (Perron & Vogelsang, 1992; Phillips & Xiao, 1998), and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) (Hornok & Larsson, 2000; Kwiatkowski et al., 1992) tests. While the DF, ADF and PP tests focus primarily on detecting the presence of a unit root, a key indicator of nonstationarity, the KPSS test directly assesses the stationarity of the series, including the identification of any deterministic trends (Afriyie et al., 2020; Choi & Phillips, 1993; Costantini & Sen, 2016; Wolters & Hassler, 2006; Zivot & Wang, 2003).

The combination of ADF and KPSS tests provides a comprehensive framework for classifying the stationarity properties of a time series. According to Dixit and Jain (2021), this dual approach allows the categorization of time series into four distinct groups: strictly stationary, stationary only in the mean (deterministic trend), stationary only in the variance (stochastic trend), and strictly non-stationary. If a time series is non-stationary in its stochastic trend, appropriate differencing techniques can be used to make the series stationary.

2.2. Differentiation of time series

The two primary approaches to differentiating a nonstationary time series are full and fractional differentiation.

A series is said to be integrated of order $d$denoted as $I(d)$if it requires differencing $d$times to reach stationarity (Batabyal et al., 2023). If $d$is a non-zero natural number, the process is called full or classical differencing.

The first-time differentiated series $(1-L)\,x_t$ is the series of increases in y_t, while the twice differentiated series $(1-L)^2\,x_t = (1-L)(x_t - x_{t-1}) = x_t - 2x_{t-1} + x_{t-2}$ is the series of increases of $(1-L)\,x_t$. The time-lag operator L used is then defined as follows:

$$L^n(x_t) = x_{t-n}, n \in \mathbb{N} \tag{6}$$

The difference operator of the order $d$denoted Δ^{d}, is a linear operator such that

$$\Delta^d \mathrm{x}_t = \mathrm{x}_t - \mathrm{x}_{t-d} = (1-L)^d\, x_t \tag{7}$$

This type of differencing is used in the ARIMA model, where an $ARIMA(p,d,q)$is a process in which the difference of order $d$is an $ARMA(p,q)$(Hamaker & MH Manuel Haqiqatkhah, 2024; V. A. Reisen, 1994).

While differencing is critical to achieving stationarity, the use of full integer differencing can sometimes unduly reduce the intrinsic memory of the series, thereby impairing its predictive ability (Park & Sung, 1994; Zhukov et al., 2024). This challenge motivates the use of fractional differencing (FD) to determine the optimal order $d$which induces stationarity (Batabyal et al., 2023; Flores-Muñoz et al., 2019).

López de Prado (2018) initially proposed the concept of fractionally differentiated features to find the most appropriate balance between zero differentiation and fully differentiated time series. The goal is to achieve stationarity in the time series, while preserving its inherent memory and predictive power. The Backshift Operator $L$is considered and applied to the time series $\{x_t\}$of functions such that $L^k x_t = x_{t-k}$. The difference between the current and last feature value can be expressed as $(1-L)_t^X$. For a positive integer $n$it also holds that:

$$(x+y)^2 = \sum_{k=0}^{n} \binom{n}{k} x^k y^{n-k} = \sum_{k=0}^{n} \binom{n}{k} x^{n-k} y^k \tag{8}$$

Furthermore, for any number d, the equation:

$$(1+x)^d = \sum_{k=0}^{\infty} \binom{d}{k} x^k \tag{9}$$

is the binomial series.

In a model where $d$can be a real number, the binomial series can be expanded into a series of weights $w$in equation 9:

$$\omega = \left\{1, -d, \frac{d(d-1)}{2!}, \frac{d(d-1)(d-1)}{3!}, \dots, (-1)^k \prod_{i=0}^{k-1} \frac{d-i}{k!}\right\} \tag{10}$$

This coefficient $d$is the amount of memory that must be eliminated to achieve stationarity. For a unit root $d < 1$ while for explosive behavior $d > 1$.

3. FORECASTING MODELS

In this work, two forecasting paradigms, statistics and deep learning (DL), are used to conduct experiments. On the statistical side, ARIMA, which utilizes classical (full) differentiation, and ARFIMA, which incorporates fractional differentiation, are used and compared. For deep learning, the LSTM model is applied to the time series. In addition to LSTM, a novel model called FD-LSTM is proposed and used, which first applies fractional differentiation to the time series in the preprocessing phase before prediction with LSTM. The models are described in detail in the following subsections.

3.1. ARIMA

An Autoregressive Integrated Moving Average process of order $p, d, and\ q$ for a series $\{y_t\}$, denoted $ARIMA(p,d,q)$, is a process of the following form:

$$\left(1 - \phi_1 L - \dots - \phi_p L^P\right)\Delta^d x_t = (1 - \theta_1 L - \dots - \theta_q L^q)\, \varepsilon_t \tag{11}$$

or

$$\left(1-\phi_1 L - \ldots - \phi_p L^P\right)(1-L)^d x_t = (1-\theta_1 L - \ldots - \theta_q L^q)\,\varepsilon_t \tag{12}$$

L is the lag operator such that $Lx_t = x_{t-1}$ and $L^p x_t = x_{t-p}\Delta^d$ is the difference operator of degree d, a natural number. $\left(\phi_1, \ldots, \phi_p\right)$ and $(\theta_{1,\ldots,}\theta_q)$ are coefficients to estimate, and $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.

Thus, ARIMA and Seasonal ARIMA are stationary series models with a trend and stochastic seasonality (Hamaker & MH Manuel Haqiqatkhah, 2024; V. A. Reisen, 1994; Somboonsak, 2020; Swaraj et al., 2021).

3.2. ARFIMA

The ARFIMA (Autoregressive Fractionally Integrated Moving Average) model provides a more nuanced approach to maintaining data stationarity while maximizing memory retention (Lardic & Mignon, 1999; K. Liu et al., 2017; V. Reisen et al., 2001, p. 202, 2001). Thus, ARFIMA focuses on extended memory operations and is formally specified as:

$$\phi(L^p)(1-L)^{-d}(y_t - x_t\beta) = \theta(L^q)\varepsilon_t \tag{13}$$

where:

$$\phi(L^p) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$$

$$\theta(L^q) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$$

$$(1-L)^d = \sum_{i=0}^{\infty} (-1)^i \frac{\Gamma(i+d)}{\Gamma(i+1)\Gamma(d)} L^i$$

The lag operator L is defined as $L^i y_t = y_{t-i}$, $t = 1, .., n$ and $i = 1, .., t-1$; $\varepsilon_t \sim iid(0, \sigma^2)$, $\Gamma(.)$ is the gamma function.

$ARFIMA(p, d, q)$ is a process with long memory when $d \in]-{}^1/_2, {}^1/_2[$ and $d \neq 0$. They are invertible if $d > -1/2$ and stationary if $d < 1/2$ (Andrysiak & Saganowski, 2015).

More specifically, three cases can be distinguished:

- If $0 < d < 1/2$, the process is stationary with long memory;
- If $d = 0$, the ARFIMA process is reduced to the standard ARMA process;
- If $-1/2 < d < 0$, the process is anti-persistent. The autocorrelations decrease hyperbolically towards zero, alternating in sign, known as the Joseph effect (Satyaveer et al., 2023).

3.3. LSTM

Long short-term memory (LSTM) is a type of recurrent neural network (RNN) designed to overcome the vanishing gradient problem and capture long-term dependencies. LSTM cells have memory units that can store and retrieve information over long periods of time (Ajagbe & Adigun, 2024; Batoure Bamana et al., 2025; Brownlee, 2018; Chimmula & Zhang, 2020; Nuanchuay & Sinthupinyo, 2022). LSTM gates (input, forget, output) use sigmoids to modulate information flow. The three gates of the LSTM network are shown as

$$\begin{cases} J_t = sigmoid(w_J[h_{t-1}, k_t] + b_J) \\ G_t = sigmoid(w_G[h_{t-1}, k_t] + b_G) \\ P_t = sigmoid(w_P[h_{t-1}, k_t] + b_P) \end{cases} \tag{14}$$

In equation 14, $J_t$is the function of the input gate; $G_t$is the function of the forget gate, and $P_t$is the output gate function. $W_x$are the coefficients of the neurons at gate (x), $h_{t-1}$is the result of the previous time step, $h_t$is the input to the current function at time step $t$and $b_x$is the bias of the neurons at gate (x). The input gate in the first equation represents the information to be stored in the cell state. The second equation represents the information derived from the activation output of the forget gate. In contrast, the third equation, which governs the output gate, integrates the cell state information with the output of the forget gate at step t to generate the final output.

3.4. Fractional differentiation and LSTM

This study introduces a novel forecasting model, FD-LSTM, which integrates fractional differentiation and LSTM. Fractional differentiation, as described in Section 2.2, transforms the original time series into a stationary one while preserving its long-term memory. The stationary series is then fed into an LSTM network, as described in Section 3.3, to generate forecasts.

3.5. Forecasting metrics

The accuracy of the prediction models is measured using the root mean square error (RMSE), mean absolute error (MAE), and Pearson's linear coefficient of determination$R2$metrics (Ajagbe & Adigun, 2024; Batoure Bamana et al., 2025; Brownlee, 2018; Hodson, 2022). The RMSE (Equation 15) is the square root of the root mean square error between the predicted and actual values of the time series. The MAE (Equation 16) measures the mean absolute error between the predicted and actual values of the time series. Typically, the model with the lowest of the above measures is considered optimal. The$R2$ coefficient measures the fit of the model to the observed data based on the explained and total sums of squares. An$R2$(Equation 17) close to 1 indicates a model that is good at predicting the data. A negative$R2$indicates that the predictions are worse than the systematically predicted mean or the horizontal line.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{15}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{17}$$

Where n is the number of observations, y_i is the series value at step i, $\hat{y}_i$ is the corresponding predicted value, and $\bar{y}$ is the mean of the observations.

4. METHODOLOGY

The methodology for this experimental study involves a series of steps, from data collection to interpretation of prediction results, to ensure a comprehensive approach to model development and evaluation.

First, data are collected from a database in the form of time series, with the selected topics, collection periods, and geographic scope guiding the selection process. After an initial screening to remove missing values, outliers, or typographical errors, each time series is subjected to stationarity tests (ADF and KPSS) and then classified based on the results. Time series identified as having a unit root (indicating non-stationarity with a stochastic trend) are selected for differencing and subsequent forecasting analyses. Both integer and fractional approaches are used. ARIMA models are fitted for integer differencing by determining $p$and $q$parameters that minimize the Akaike Information Criterion (AIC). Based on these $p$and $q$values, along with a fractional differentiation parameter dARFIMA models are specified. Furthermore, the LSTM deep learning model is applied to fractionally differenced time series via an FD-LSTM framework, while a baseline LSTM model is applied to the original time series. Prediction metrics RMSE, MAE and$R2$are collected for all four models and used to draw detailed conclusions and recommendations.

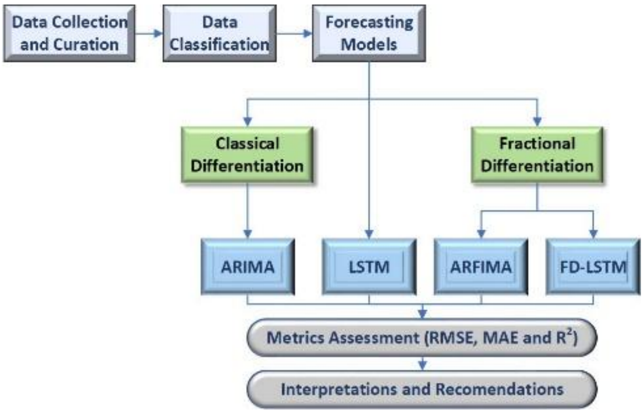

Fig. 1. Research methodology

Figure 1 illustrates the proposed approach. The type of differentiation is first illustrated for each prediction model in which it is used. These steps guide the experimental phases.

5. EXPERIMENTS AND RESULTS

Experiments are conducted using the scientific programming language Python in the Google Colaboratory environment (Python Software Foundation). Data is first described and classified before prediction is initiated.

5.1. Data collection and curation

The data for this work is collected from the DHIS (District Health Information Software) platform established by the Cameroon Ministry of Public Health and managed by the Health Information Unit (Ministry of Public Health Cameroon, 2023). This platform contains data on several diseases collected at the health facility level and aggregated weekly to provide information at the area, district, and regional levels (Moskolaï Ngossaha et al., 2024).

The programmatic health map for 2023-2025 shows that Cameroon comprises ten health regions, which are subdivided into health districts (Ministry of Public Health Cameroon, n.d.). Adamawa is one of ten regions located at the transition between the warm northern and cool southern parts of the country. The region is a suitable working sample representative of the country as a whole. Adamawa Region includes 11 health districts: Bankim, Banyo, Belel, Dang, Djohong, Meganga, Ngaoundal, Ngaoundere Rural, Ngaoundere Urbain, Tibati, and Tignere.

Data are selected according to the disease, time period, and geographic scale required. For the present work, the data concern malaria and typhoid fever, classified as diseases with epidemiologic potential, as well as the causes of multiple deaths in the region and subregion (Hancuh et al., 2023; Mbishi et al., 2024; Sohanang Nodem et al., 2023). The study period is from January 2021 to December 2023 (3 years). The dataset includes 11 series for malaria and 11 for typhoid for each of the 11 health districts in the region. In addition, there is one series for each disease for the entire region. The dataset thus contains 24 series for experimentation, each containing 156 recorded observations. Since there are no anomalies in the data sets, further steps can be performed.

5.2. Data classification

The ADF and KPSS tests are performed on each of the 24 series for classification purposes. The first test aims to detect the presence of a unit root in the series and thus draw a conclusion for stationarity with a stochastic trend. KPSS tests for stationarity with a deterministic trend in a time series. The stochastic trend, determined by the ADF test, is of most interest to this work because the time series requires differentiation to be stationary. As the null hypothesis, the ADF test posits the presence of a unit root, hence non-stationarity. The null hypothesis is rejected for a $p-value < 0.05$ (5%). For the KPSS test, the null hypothesis is the stationarity of the time series. If $p-value < 0.100$, the series is considered non-stationary with a deterministic trend. Table 1 summarizes the results of the ADF and KPSS tests performed on the time series. The values in bold are those where the time series exhibit non-stationarity.

Tab. 1. ADF and KPSStests on time series

Time series of Health Area	Malaria		Typhoid Fever	
	ADF Test	KPSS Test	ADF Test	KPSS Test
Bankim	**21.42%**	> 0.1000	**94.45%**	**< 0.0100**
Banyo	**26.01%**	> 0.1000	**9.97%**	> 0.1000
Belel	**44.45%**	**< 0.0100**	**27.20%**	**< 0.0100**
Dang	**31.01%**	> 0.1000	0.05%	**= 0.0707**
Djohong	**8.38%**	> 0.1000	**98.78%**	**= 0.0399**
Meiganga	**29.23%**	**= 0.0163**	0.01%	> 0.1000
Ngaoundal	**48.29%**	> 0.1000	4.87%	> 0.1000
Ngaoundere Rural	0.52%	> 0.1000	0.38%	**= 0.0432**
Ngaoundere Urbain	0.25%	> 0.1000	0.00%	> 0.1000
Tibati	**21.88%**	**< 0.0100**	1.80%	< 0.0100
Tignere	0.94%	**= 0.0307**	0.00%	> 0.1000
Adamawa Region	**34.25%**	> 0.1000	**16.89%**	**= 0.0937**

Of these series, 14 out of 24 (09 series for malaria and 05 series for typhoid) are non-stationary with stochastic trend. 11 out of 24 series (04 for malaria and 07 for typhoid) are non-stationary with deterministic trend. 07 out of 24 series (03 for malaria and 04 for typhoid) are strictly non-stationary, and 06 out of 24 (02 for malaria and 04 for typhoid) are fully stationary. In the following steps, 14 out of 24 series are non-stationary in the stochastic trend and are therefore considered for differentiation. Classical differentiation is performed first, followed by fractional differentiation.

5.2.1. First-order differentiation

After applying first-order differencing, all 14 series are stationary, eliminating the need for higher-order differencing. Table 2 shows the p-values confirming the stationarity of the differenced series and the correlation coefficients (Ahsan et al., 2020; Yuan & Shou, 2022) comparing each original series with its differenced counterpart. In Table 2, N/A stands for Not Applicable, indicating that the typhoid series is already stationary. The table groups the data for malaria and typhoid fever, considering only non-stationary time series (09 for malaria and 05 for typhoid fever).

Tab. 2. Classical differentiation and correlation with the initial series

Times series of Health Area	Malaria		Typhoid Fever	
	ADF Test	Correlation	ADF Test	Correlation
Bankim	0.00%	0.30	0.00%	0.34
Banyo	0.00%	0.41	0.00%	0.35
Belel	0.00%	0.42	0.00%	0.53
Dang	0.00%	0.28	N/A	N/A
Djohong	0.01%	0.26	0.00%	0.38
Meiganga	0.00%	0.28	N/A	N/A
Ngaoundal	0.00%	0.26	N/A	N/A
Tibati	0.00%	0.27	N/A	N/A
Adamawa Region	0.00%	0.18	0.00%	0.22

Among the 14 differentiated first-order series, only the Belel (typhoid) data have a correlation above 0.5(exactly 0.53) with its original series. For the others, the correlations typically range from 0.2and 0.4. Notably, the Adamawa Region (Malaria) series has a correlation of only 0.18. These values indicate a significant divergence between each time series and its differentiated counterpart, reflecting significant memory loss.

5.2.2. Fractional order differentiation

Table 3 provides information on the fractional differentiation order for each non-stationary time series. This order is the smallest real d for which the series becomes stationary, obtained by applying the appropriate optimized Python codes. The resulting differentiated time series is tested for the presence of a unit root by ADF, and the Pearson correlation coefficient with the original series is calculated.

Two series, Bankim ($d = 0.78$) and Djohong ($d = 0.86$), have a fractional differentiation parameter $d \geq 0.5$for typhoid fever. The remaining series have $0 < d \leq 0.5$and are classified as having long memory. None of the time series has a negative $d$is equal to or greater than 1. The ADF $p - values$for the fractionally differentiated series are all below 5%indicating that the unit root is no longer present after differentiation, confirming the stationarity of these series. Most of the correlation values (12 out of 14) between the fractionally differentiated series and their original series are above 0.75. However, Bankim (0.51) and Djohong (0.46) for typhoid fever are the exceptions, with a correlation of $0.75$with their original time series. These results suggest that fractional differentiation maintains a strong correlation with the original series, as opposed to full differentiation, which often results in a weaker relationship. In Table 3, N/A stands for Not Applicable, which means that the typhoid series is already stationary.

Tab. 3. Fractional differentiation of order d, ADF test, and correlation with initial series

Health Area	Malaria			Typhoid Fever		
	d	ADF test	Correlation	d	ADF test	Correlation
Bankim	0.22	4.73%	0.95	0.73	4.64%	0.51
Banyo	0.37	4.87%	0.83	0.14	4.44%	0.98
Belel	0.43	4.86%	0.76	0.15	4.43%	0.97
Dang	0.20	4.91%	0.96	N/A*	N/A	N/A
Djohong	0.34	2.87%	0.87	0.86	4.43%	0.46
Meiganga	0.41	4.99%	0.78	N/A	N/A	N/A
Ngaoundal	0.29	4.81%	0.91	N/A	N/A	N/A
Tibati	0.29	0.70%	0.90	N/A	N/A	N/A
Adamawa Region	0.33	4.94%	0.89	0.32	4.53%	0.90

Once series are differentiated, predictions can be performed, evaluated and compared.

5.3. Forecasting

Four forecasting models are selected. All-time series considered at this stage have a non-stationary stochastic trend (i.e., contain a unit root). The models fitted are ARIMA, ARFIMA, the proposed FD-LSTM, and the standard LSTM as a baseline for comparison.

The ARMA model is applied to the time series after differentiation to order 1 to determine the appropriate p and q parameters with the lowest AIC (Akaike Information Criterion). The resulting ARIMA models have parameters (p, 1, q). The ARFIMA model is applied to the time series differentiated at the fractional order d, using the parameters p and q of the ARMA model. This action results in an ARFIMA-like (p, d, q) model. The value of d is obtained by applying the appropriate Python code. Similarly, the LSTM model is applied to the fractionally differentiated time series, yielding the FD-LSTM model. For both the baseline LSTM and the proposed FD-LSTM, we used the same architecture: a single LSTM layer with 50 hidden units (return_sequences=False, default tanh/sigmoid activations), followed by a fully connected output layer with one neuron (linear activation) to predict the next value. No dropout or recurrent dropout was applied. Each univariate series was framed as a supervised learning problem with a fixed input window of 12 past observations and a one-step-ahead prediction horizon (sliding window, stride = 1). The data sets were split chronologically (80% training, 20% testing) without shuffling. Inputs were standardized (z-score) using only the training portion; predictions were inverse-transformed before computing RMSE, MAE, andR2. Models were trained with Adam (learning rate10-3, mean squared error loss, batch size 16, and 50 epochs (no early stopping), using the same random seed for weight initialization and windowing to ensure repeatability. FD-LSTM differs in its preprocessing: before windowing, the series is fractionally differenced with the order ddd estimated on the training data (unit root removal criterion), using binomial weight recursion, truncated when |wk| <10-5; the same transformation is then applied to the test data with the training-derived parameters. All other settings, including scaling and LSTM architecture, are identical for LSTM and FD-LSTM.

Once the predictions are made, the accuracy metrics are harvested for analysis and comparison.

5.4. Evaluating and comparing forecasting performances

Each time series dataset is divided into 80% for training and 20% for testing. The performance metrics of the models (RMSE, MAE, andR2) are summarized in Tables 4 through 17, for a total of 14 tables.

Tab. 4. Evaluation metrics for Bankim time series (Malaria)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(0,1,1)	40.85	29.60	0.58	261.37	202.14	-0.42
ARFIMA(0,0.22,1)	27.99	22.30	0.81	4.50	3.46	0.99
FD-LSTM	4.46	3.51	0.99	15.67	12.99	0.99
LSTM	52.87	42.99	0.30	197.82	152.21	0.20

Tab. 5. Evaluation metrics for Banyo time series (Malaria)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(0,1,1)	40.72	29.17	0.39	124.14	94.46	-0.10
ARFIMA(0,0.37,1)	13.13	10.38	0.93	2.14	1.33	0.99
FD-LSTM	3.46	2.73	0.99	8.79	6.57	0.99
LSTM	43.18	36.05	0.31	106.99	77.35	0.19

Tab. 6. Evaluation metrics for Belel time series (Malaria)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(0,1,1)	22.45	16.86	0.19	20.42	16.54	-0.46
ARFIMA(0,0.43,1)	0.00	0.00	1.00	0.00	0.00	1.00
FD-LSTM	3.10	2.46	0.98	1.83	1.47	0.98
LSTM	22.76	18.45	0.17	31.36	28.13	-2.64

Tab. 7. Evaluation metrics for Dang time series (Malaria)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(0,1,1)	50.16	35.69	0.54	225.57	170.58	-0.45
ARFIMA(0,0.20,1)	36.52	27.50	0.76	8.46	6.04	0.99
FD-LSTM	10.41	7.82	0.98	22.97	20.73	0.96
LSTM	62.74	46.12	0.29	159.99	134.05	0.27

Tab. 8. Evaluation metrics for Djohong time series (Malaria)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(0,1,0)	38.84	28.18	0.84	310.60	177.15	-0.11
ARFIMA(0,0.34,0)	40.16	30.06	0.83	7.83	5.83	0.97
FD-LSTM	7.11	5.41	0.99	27.36	17.63	0.71
LSTM	68.99	60.29	0.50	203.26	127.36	0.53

Tab. 9. Evaluation metrics for Meiganga time series (Malaria)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(1,1,0)	58.96	41.47	0.69	79.92	58.28	-0.01
ARFIMA(1,0.41,0)	32.83	26.01	0.90	5.60	4.03	0.96
FD-LSTM	13.10	10.35	0.98	15.90	10.00	0.79
LSTM	78.17	66.08	0.45	107.21	98.05	-0.78

Tab. 10. Evaluation metrics for Ngaoundal time series (Malaria)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(2,1,0)	77.17	48.41	0.71	470.22	334.49	-0.92
ARFIMA(2,0.29,0)	64.61	40.01	0.80	14.67	10.95	0.99
FD-LSTM	10.36	6.11	0.99	20.16	17.42	0.99
LSTM	114.91	75.00	0.37	290.82	238.64	0.26

Tab. 11. Evaluation metrics for Tibati time series (Malaria)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(2,1,1)	43.70	30.71	0.58	42.00	34.99	-1.37
ARFIMA(2,0.29,1)	23.44	18.65	0.87	6.69	5.3	0.93
FD-LSTM	9.41	7.37	0.98	5.76	4.56	0.94
LSTM	68.72	58.89	-0.02	114.22	111.23	-17.21

Tab. 12. Evaluation metrics for Adamawa Region time series (Malaria)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(0,1,0)	349.37	226.47	0.74	1859.48	1423.87	-0.44
ARFIMA(0,0.33,0)	285.51	223.95	0.83	73.50	51.00	0.99
FD-LSTM	115.23	90.42	0.97	248.45	231.15	0.94
LSTM	496.44	400.72	0.48	1108.97	1020.30	0.49

Tab. 13. Evaluation metrics for Bankim time series (Typhoid Fever)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(2,1,1)	13.36	10.42	0.11	93.65	66.49	-0.55
ARFIMA(2,0.73,1)	6.71	5.13	0.76	0.43	0.21	1.00
FD-LSTM	0.78	0.61	0.99	2.81	1.62	0.99
LSTM	14.76	11.40	-0.07	101.66	72.24	-0.81

Tab. 14. Evaluation metrics for Banyo time series (Typhoid Fever)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(2,1,1)	21.71	15.71	0.09	100.73	70.20	-0.29
ARFIMA(2,0.14,1)	8.23	6.63	0.87	1.55	0.98	0.99
FD-LSTM	1.35	1.08	0.99	5.12	4.25	0.99
LSTM	21.65	17.82	0.10	83.73	64.86	-0.04

Tab. 15. Evaluation metrics for Belel time series (Typhoid Fever)

Model / Metrics	Training			Testing		
	RMSE	MAE	R^2	RMSE	MAE	R^2
ARIMA(0,1,1)	4.38	3.31	0.17	6.36	5.23	-0.01
ARFIMA(0,0.15,1)	1.28	1.09	0.92	0.25	0.22	0.99
FD-LSTM	0.77	0.59	0.97	0.94	0.77	0.94
LSTM	4.66	3.69	0.07	7.33	5.54	-0.31

Tab. 16. Evaluation metrics for Djohong time series (Typhoid Fever)

Model / Metrics	Training			Testing		
	RMSE	MAE	R²	RMSE	MAE	R²
ARIMA(0,1,1)	8.80	7.01	-0.13	60.11	34.20	-0.33
ARFIMA(0,0.86,1)	6.72	5.38	0.34	0.68	0.24	0.99
FD-LSTM	1.41	1.12	0.97	5.28	3.48	0.82
LSTM	8.22	6.52	0.00	60.10	34.42	-0.30

Tab. 17. Evaluation metrics for Adamawa Region time series (Typhoid Fever)

Model / Metrics	Training			Testing		
	RMSE	MAE	R²	RMSE	MAE	R²
ARIMA(0,1,0)	86.56	60.09	0.59	422.62	315.28	-0.51
ARFIMA(0,0.32,0)	53.03	37.80	0.85	9.13	6.50	0.99
FD-LSTM	10.78	7.82	0.99	23.69	21.05	0.98
LSTM	107.60	76.30	0.37	317.57	245.72	0.15

The analysis of the prediction metrics data provides two directions for comparison, statistical and deep learning, as summarized in Table 18. Performance percentages are determined for both the training and test sets.

Tab. 18. Forecasting scores comparison

Models' comparison	Training	Testing
ARFIMA outperforms ARIMA	13/14 (~93%)	14/14 (100%)
FD-LSTM outperforms LSTM	14/14 (100%)	14/14 (100%)

6. DISCUSSION AND CONCLUSIONS

The implementation of this experimental study, which addressed non-stationarity with a stochastic trend in the context of limited data, has highlighted significant results. A total of 24 series were used to assess the impact of the differentiations on both the time series and the accuracy of the predictions. The dataset includes weekly malaria and typhoid cases between 2021 and 2023 from health districts in the Adamawa region of Cameroon. Notably, this public health dataset is relatively small, highlighting the challenges inherent in analyzing limited data resources that are often non-stationary. A comprehensive literature review was first conducted to clarify the directions and contributions of the study. The theoretical foundations of stationarity, including its types, relevant tests, and differencing techniques, are then presented to lay the groundwork for the modeling approach. For forecasting, ARIMA, ARFIMA and LSTM are used in addition to the proposed FD-LSTM models. The performance of the models is evaluated and compared using the RMSE, MAE, and R2 metrics. Classification using the ADF and KPSS tests revealed that 14 of the 24 series had a stochastic trend (hence a unit root). 11 were non-stationary in their deterministic trend, and 7 were found to be completely non-stationary. Applying first-order integer differencing to the 14 stochastically non-stationary series made them stationary. However, the correlations with the original series are low (mostly between 0.2 and 0.4).

In contrast, fractional differencing achieved stationarity for all series while preserving stronger correlations (typically ranging from 0.75 to 0.98). In addition, most of the fractionally differentiated series fell within orders d between 0.1 and 0.5, indicating a substantial long-range memory component. Each time series is divided into training (80%) and testing (20%) in the prediction phase. Evaluation metrics are computed and collected for each model across both datasets. A pairwise comparison of statistical and deep learning methods shows that in the statistical category, ARFIMA consistently outperformed ARIMA in both training and testing. In the deep learning category, FD-LSTM outperformed LSTM 100% of the time on both datasets.

These results highlight the importance of preprocessing time series data, specifically through differencing, before performing prediction or other analyses. Fractional differencing yields better results than integer differencing because it preserves more of the long-term memory of the time series. No work has adopted the present approach from the bibliographic research, even using this dataset. The work produced statistical results consistent with the initial hypothesis, which was formulated as follows: the application of fractional differentiation can improve prediction accuracy for datasets with limited data. The limitations of this work are mainly the use of a single dataset and in a single domain (public health). Future work will be extended to other domains and datasets to consolidate the results. Furthermore, the experiments can be extended to other machine learning or deep learning approaches. Nevertheless, the results are sufficient for first conclusions.

Recommendations from this research highlight the value of prioritizing fractional differencing in time series preprocessing. These approaches have been shown to improve forecast accuracy even for constrained, irregular, and limited-volume datasets. Furthermore, extending the application of these results to domains such as industrial, engineering, economic, financial, environmental, and natural hazards, where comparable data characteristics prevail, may yield similarly improved predictive results.

Subsequent research plans to refine the proposed approach by integrating fractional differencing with multiple changepoint detection methods. It is also planned to investigate additional deep learning frameworks, as well as different datasets and domains, to evaluate how these methods can improve predictive performance in complex and evolving datasets.

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Conflicts of Interest

The authors have no competing interests to declare relevant to this article's content.

Data Availability Statement

Data supporting the findings of this study and codes are available from the corresponding author upon reasonable request.

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