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A Three-Step nonparametric change point detection method using A Meta-Heuristic algorithm for analyzing inflation trends in Nigeria (2019-2023)

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Abstract

CPD is a statistical technique that finds the change points in data sequences where the statistical properties of the data have shifted. This technique has valuable applications in the field of economics as well as finance, and public health. In this study a CPD methodology is developed by proposing an enhanced three-step nonparametric approach based on the existing two-step method. The proposed framework couples Kernel Conditional Density Estimation with Fourier features and machine learning techniques for the precise identification and classification of change points. Data preprocessing for smoothness and noise reduction will be included, followed by KCDE-F for conditional density estimation, and then a machine-learning classifier refines the sensitivity and specificity of the detected change points. This paper identifies critical change points in Nigerian inflation dynamics using data from 2019 to 2023. The result shows that the developed the three-step procedure for change point detection presented here is not only also capable in change point detection but also in the estimation of structural breaks in time-series data. The wide applicability of this methodology is envisioned to extend beyond economics into other domains where the need for change point detection is compelling.

Keywords: Change Point Detection; Kernel Conditional Density Estimation; Machine Learning; Time Series Analysis; Inflation Trends; Structural Shifts.

1. Introduction

Change Point Detection (CPD) is a method of finding the points in a sequence of data where the statistical properties-mean, variance, or distribution-undergo a significant change (Lavielle, 2005). Those kinds of points are called "change points" and reflect the shift in the underlying process that generates data. Its applications can be found in many areas, such as detecting structural breaks regarding GDP growth or inflation trends as an indicator of economic shifts or policy impacts (Bai & Perron, 2003; Lavielle, 2005). Recognizing change points in finance could provide indications of transitions within stock markets or economic cycles that were characteristic of financial instability; this would thus allow for the realization of proactive risk management strategies (Adams et al., 2021). Applications in health might track the changing pattern of some diseases or treatment effectiveness, informing enhanced responses to public health (Zhou et al., 2020).

In practice, these change points are usually obtained mathematically through the optimization of a log-likelihood that has been regularized over different segmentations. The foundation of this approach was established through experiments that involved altering the mean of independent univariate Gaussian variables with constant variance at an unspecified point, as conducted by Ewan (1955). A number of years afterward, works were being conducted on this approach by different researchers, among them is Frick et al. (2014), Fryzlewicz (2014), and Pein et al. (2017). This research, seeks to improve on the two-step method used by Londschien, Bühlmann, and Kovács, (2023) in developing a three-step nonparametric change point detection method. The algorithm of the developed method is then converted into a program and in conjunction with a machine learning algorithm (used as a data classifier); its workability in detecting change points is tested on a time-series data that reveals inflation trends in Nigeria from 2019-2023. The study then provides some insight into how economic policies and external shocks affect inflation dynamics in the country.

2. Literature Review

2.1 Recent and Past Endeavors on Change Point Detection

Change point detection techniques that are nonparametric in nature often utilize measures that do not depend on parametric forms of the kind of change or the distribution. The work of Pettitt (1979) pioneered the use of nonparametric change point detection methods followed by the work of Carlestein (1988), Dumbgen (1991), Zou et al. (2014) and Madrid-Padilla et al. (2021a). In nonparametric senerios, the multivariate approach can be quite challenging. The only well-known types of nonparametric change point detection methods are those that are kernel-density based (Madrid-Padilla et al., 2021b), kernel-distances based (Arlot et al., 2019; Garreau and Arlot, 2018; Chang et al., 2019) including those that are rank-based (Lung-Yut-Fong et al., 2015) and those simply based on just distances (Matteson and James, 2014; Chen and Zhang, 2015; Zhang and Chen, 2021). These methods these methods are capable of maximizing a test statictic tat evaluates the differences between distributions for a single change point. In recent times Machine learning methods are now being uses with nonparametric methods in anyalsing complex probability distributions related to conditional classes (Breiman, 2021), providing more accurate results as regards the definite points of change in the data than distance-based methods. In this context, multivariate nonparametric methods for detecting multiple change points are employed, utilizing the two-sample testing approach with binary classifiers as introduced by Friedman (2004) where developed using Random Forest (Hediger et al., 2022; Londschien, Bühlmann, and Kovács, 2023) while considering a similar method developed by Lopez-Paz and Oquab (2017) which combines Friedman's method with neural networks.

2.2 The Nature of Inflation in Nigeria

In Nigeria, inflation has been a persistent economic problem that has been characterized by wide fluctuations and complicated patterns. To understand its nature, one must look at historical trends, underlying causes, and the socioeconomic impacts on the nation. Over the last decades, Nigeria has witnessed both high and low inflation. In 2017, inflation in Nigeria exceeded 16%, higher than the average for African and Sub-Saharan countries. The attendant volatility often became the precursor of deeper economic ailments that caused fluctuating prices, increased unemployment rates, and greater poverty. Inflation in Nigeria soared to a 28-year high in December 2024, fueled by a weakening currency and soaring food prices. Jumps in the prices of essential commodities like wheat and cooking oil have further stoked the cost-of-living crisis. (Reuters, December 16, 2024). High inflation significantly impacts low-income households, diminishing their purchasing power. At least 67 people died in stampedes during charity events in December 2024, which are connected with the dire cost-of-living crisis that emanated from the unstable economy. (AP News, 2024, December 26). Alterations in the money supply and government expenditure considerably influence inflation rates in Nigeria. Increases in government spending, especially deficit spending, can lead to currency depreciation and an expansion of the money supply, which can exacerbate inflation (Asogu, 2021). The importation of products is another element that affects the rate of inflation. Nigeria is vulnerable to changes in world prices because it is a net importer. Changes in import costs, especially for necessities, could lead to inflation at home. In addition to the reasons mentioned, poor infrastructure, shortage of energy and agricultural related issues may paralyze supply chains which thereby enhance the price of production, and hence the price. Further, devaluation of the Naira raises the prices of imported goods that lead to inflation. The central bank of Nigeria has taken some measure in maintaining the stability of the currency, controlling inflation index accordingly (Moser, 1995).

The Nigerian government has implemented several measures to combat inflation, including raising interest rates to lessen inflationary pressures, removing gasoline subsidies to reduce budget deficits (which has led to higher transportation costs), and allowing the Naira to fluctuate more freely to stabilize the currency and reflect real market values (Reuters, 2024; October 29).

Nigerian inflation is a complicated topic that is influenced by both internal and international economic conditions and structural problems. A comprehensive approach that balances monetary policy, structural changes, and fiscal discipline is required to address it and provide stability and long-term economic growth. In this research work we employ a time series covering inflation records from the National Beareu of Statistics (NBS, 2024). We develop a program in python using a nonparametric change point detection method, and a Kenelized version of the Random Forest Machine Learning algorithm called Kernel Conditional Density Estimation Forests (KCDE-F) combines decision tree-based ensemble models such as, Random Forests with Kernel Density Estimation (KDE) to estimate conditional probability density functions (PDFs). It to be suitable for this study since it focuses on a target variable (inflation) given a set of features. Although KCDE-F is computationally expensive this has been balanced by using it on a smaller amount of time-series data of one year instead of several years, thus reducing the depth of trees in the forest and the number of splits and density calculations. Also, the three-step search used in this study as enumerated in the methodology section greatly reduces the number of classifier fits thereby reducing computational cost.

2.3 Consumer Price Index (CPI)

The Consumer Price Index serves as a crucial economic indicator, illustrating the average fluctuations in consumer prices over time for a selected group of goods and services. Because it reflects cost of living and purchasing power in an economy, it acts like a measuring tool for inflation. Based on findings by the U.S. Bureau of Labor Statistics (2024), the CPI shows changes in the prices of a basket of goods and services over a period of time, serving as a critical pointer for inflation monitoring, however, despite its pervasiveness, however, the CPI has some significant problems in accurately reflecting consumer behavior and quality changes in goods and services. The improvements in data collection and analysis continuously overcome these problems so that the CPI would be a correct measure of inflation. The CPI is calculated using the formula:

$$CPI = \frac{\text{Cost of Market Basket in Current Year}}{\text{Cost of Market Basket in Base Year}} \times 100$$

Where: Cost of Market Basket in Current Year is the total cost of a fixed basket of goods and services in the current year and Cost of Market Basket in Base Year: The total cost of the same basket of goods and services in the base year. The result is often expressed as an index.

3. Methodology

3.1 Development of Proposed Nonparametric Change Point Detection Method

This methodology used in this study is built on studies carried out by Londschien, Bühlmann, and Kovács, 2023, where the solution to a nonparametric estimator (1) was found by evaluating the classifier loglikelihood ratio (2) for all possible candidate segmentations $\alpha \in \mathcal{A}$ is infeasible. To do this, an effective binary segmentation-based search method that approximates the solution to (1) was used. The method also involved the use of the random forest algorithm as classifiers thus bringing about the changeforest algorithm as shown in Section 3.1.

$$\hat{\alpha}_\gamma \in \underset{\alpha \in \mathcal{A}}{\operatorname{argmax}}\, G((x_i)_{i=1}^n \mid \alpha, \hat{p}) - |\alpha| \quad (1)$$

$$G((x_i)_{i=1}^n \mid \alpha, \hat{p}) := \sum_{k=1}^{K} \sum_{i=\alpha_{k-1}+1}^{\alpha_k} \log\left(\frac{n}{\alpha_k - \alpha_{k-1}} \hat{p}_\alpha(x_i)_k\right) \quad (2)$$

3.1.1 Binary segmentation

A common greedy approach for obtaining an approximate solution to the parametric maximum log-likelihood estimator (3) is binary segmentation (Vostrikova, 1981). The log-likelihood estimator (3) is expressed as:

$$\hat{\alpha}_\gamma \in \underset{\alpha \in \mathcal{A}}{\operatorname{argmax}} \max_{\vartheta_1,\ldots,\vartheta_K} \ell\left((x_i)_{i=1}^n \mid \alpha, (\vartheta_k)_{k=1}^K\right) - |\alpha|\gamma \quad (3)$$

For some $\hat{\vartheta}((u,v]) \in \operatorname{argmax}_\vartheta \sum_{i=u+1}^{v} \log\left(p_\vartheta(x_i)\right)$, binary segmentation recursively splits segments at the split s maximizing the gain:

$$G_{(u,v]}(s) := \sum_{i=u+1}^{s} \log\left(\frac{p_{\hat{\vartheta}((u,s])}(x_i)}{p_{\hat{\vartheta}((u,v])}(x_i)}\right) + \sum_{i=s+1}^{v} \log\left(\frac{p_{\hat{\vartheta}((s,v])}(x_i)}{p_{\hat{\vartheta}((u,v])}(x_i)}\right) \quad (4)$$

the increase in log-likelihood, until a stopping criterion is met. For change in mean, where $\hat{\vartheta}((u,v]) = \frac{1}{v-u}\sum_{i=u+1}^{v} x_i$ and $p_\vartheta(x) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}(x-\vartheta)^2\right)$, the normalized gain $\frac{2}{v-u}G_{(u,v]}(s)$ is equal to $\left(\sqrt{\frac{v-s}{s-u}}\sum_{i=u+1}^{s} x_i - \sqrt{\frac{s-u}{v-s}}\sum_{i=s+1}^{v} x_i\right)^2$, the square of the CUSUM statistic, first presented by Page (1954). Binary segmentation typically requires $\mathcal{O}(K n\log(n))$ evaluations of the gain, where K is the number of change points, and is typically faster than search methods based on dynamic programming such as PELT (Killick et al., 2012). The parametric log-likelihood ratio $G_{(u,v]}(s)$ in binary segmentation is replace with the nonparametric classifier log-likelihood ratio from (2)

$$G((x_i)_{i=u+1}^s \mid \{u,s,v\}, \hat{p}) = \sum_{i=u+1}^{s} \log\left(\frac{v-u}{s-u}\hat{p}_{\{u,s,v\}}(x_i)_1\right) + \sum_{i=s+1}^{v} \log\left(\frac{v-u}{v-s}\hat{p}_{\{u,s,v\}}(x_i)_2\right)$$
$$\approx \sum_{i=u+1}^{s} \log\left(\frac{p_{(u,s]}(x_i)}{p_{(u,v]}(x_i)}\right) + \sum_{i=s+1}^{v} \log\left(\frac{p_{(s,v]}(x_i)}{p_{(u,v]}(x_i)}\right) \quad (5)$$

In many parametric settings, the expected gain curve $G_{(u,v)}$ will be piecewise convex between the underlying change points (Kovács et al., 2020b). Proposition 3 shows that the same holds for the nonparametric variant (5) in the population case.

3.1.2 Three-Step Search Algorithm for Change point Detection

Binary segmentation relies on the full grid search, where $G_{(u,v]}(s)$ is evaluated for all $s = u+1,\ldots,v$, to find the maximizer of the gain $G_{(u,v]}(s)$. In many traditional parametric settings, such as change in mean, log-likelihoods of neighboring segments can be recovered using cheap $\mathcal{O}(1)$ updates. This enables change point detection with binary segmentation in $\mathcal{O}(K n\log(n))$ time, where K is the number of change points. In the case of numerous classifiers, especially random forests, such updates are not accessible, necessitating a complete recomputation of the classifiers. This requirement significantly increases the computational expense associated with grid search in binary segmentation. Comparable computational challenges also occur in high-dimensional regression models. To address this, Kaul et al. (2019) suggest a two-step methodology. They started with an initial guess $s^{(0)}$, fitted a single high-dimensional linear regression for each of the segments $\left(u, s^{(0)}\right]$ and $\left(s^{(0)}, v\right]$ and then generated an improved estimate of the optimal split using the resulting residuals. The procedure is executed twice, demonstrating a consistent outcome in the high-dimensional regression context with a single change point, provided that

the change point is adequately close to the first guess $s^{(0)}$. Londschien, Bühlmann, and Kovács, (2023) applied a variant of this two-step search paired with the classifier log-likelihood ratio for multiple change point scenarios. In this study, we use three-step approach - a variant of the two-step approach used by Londschien, Bühlmann, and Kovács, (2023) and instead of residuals,
we recycle the class probability predictions and the resulting classifier log-likelihood ratios for individual observations from a single classifier fit $\hat{p}_{\{u,s^{(0)},v\}}$, approximating the following expression:

$$G((x_i)_{i=u+1}^{v} \mid \{u,s,v,t\},\hat{p}) \approx \sum_{i=u+1}^{s} \log\left(\frac{v-u}{s-u}\hat{p}_{\{u,s,v\}}(x_i)_1\right) + \sum_{i=s+1}^{v} \log\left(\frac{v-u}{v-s}\hat{p}_{\{u,s,v\}}(x_i)_2\right) + \sum_{i=t+1}^{v} \log\left(\frac{v-u}{t-s^{(0)}}\hat{p}_{\{u,s,t^{(0)},v\}}(x_i)_3\right) \quad (6)$$

We call this the approximate gain. Note that the classifier and normalization factors are fixed, but the summation varies with the split s. Like Kaul et al. (2019), we compute this thrice, using the first maximizer of the approximate gain as a second guess $s^{(1)}$and using the second maximizer of the approximate gain as a third guess $s^{(2)}$. This allows us to find local maxima of the nonparametric gain (5) in a constant number of classifier fits. We start with multiple initial guesses and select the split point corresponding to the overall highest approximate gain as the third guess. The resulting three-step algorithm, as implemented in our proposed methodology (presented in Algorithm below), using three initial guesses.

Proposed Algorithm for the Three-Step Search

Input: Observations $(x_i)_{i=u+1}^{v}$, a classifier $\hat{p}$ (KCDE-F), and a minimum relative segment length $\delta > 0$.
Output: Change point estimate $\hat{\alpha} \leftarrow$ BinarySegmentation $((x_i)_{i=1}^{n}\hat{p},\delta)$.
function Binary Segmentation $((x_i)_{i=u+1}^{n}\hat{p},\delta)$.
if v − u < 2 δn then
  return ∅
end if
$\hat{s}$, $\left(\left(\ell_{i,k,j}\right)_{i=u+1,\ldots v}^{k=1,2,3}\right) j_{i=1,2,3}$ ←Three Step Search $((x_i)_{i=1}^{n}\hat{p},\delta)$.
$\hat{q} \leftarrow$ Model Selection $\left(\left(\left(\ell_{i,k,j}\right)_{i=u+1,\ldots,v}^{k=1,2,3}\right)_{j=1,2,3,\delta}\right)$
if q ≤ 0.02 then
  $\hat{\alpha}_{left} \rightarrow$ Binary Segmentation $((x_i)_{i=u+1}^{\hat{s}},\hat{p},\delta)$
  $\hat{\alpha}_{right} \rightarrow$ Binary Segmentation $((x_i)_{i=\hat{s}+1}^{v},\hat{p},\delta)$
  return $\hat{\alpha}_{left} \cup \{\hat{s}\} \cup \hat{\alpha}_{right}$
else
  return ∅
end if
end function

3.2 Data Classification Algorithm

Kernel Conditional Density Estimation Forests (KCDE-F) is an advanced non-parametric density estimation procedure in conditional densities with Fourier features is used as the classification algorithm for this study. This major reason why we choose this algorithm for our study over the usual Random forest algorithm is that, the conventional Random Forest algorithm yields only the results for regression or classification, whereas KCDE-F calculates the complete conditional density (Meinshausen, 2006). The technique of using Fourier characteristics and kernel methods is known to approximate well complicated and high-dimensional distributions. Since KCDE-F avoids the usually associated computational burden of the classical kernel techniques due to random Fourier characteristics, it applies to big data scenarios. Recent works have established that KCDE-F is robust across diverse applications, including financial risk assessment and econometric modeling, as used in the work of Sriperumbudur et al. (2022). Furthermore, Chen et al. (2023) proved that the approach works on dynamic systems whereby conditional dependencies are highly crucial. Because of its effectiveness and versatility, KCDE-F is a helpful tool in contemporary data analysis, in particular, for domains that rely heavily on precise probabilistic forecasts. The probability density function (PDF) surrounding each data point is determined by kernel density estimation (KDE), which is a component of KCDE-F. For basic implementations, KDE requires calculating the distances between each pair of points, resulting in a complexity of $O(n)^2$. The computational cost of this phase increases with the size of the dataset (n). Kernel Conditional Density Estimation with Fourier features (KCDE-F) is based on the framework of conditional density estimation, which aims to estimate the conditional probability density function $p(y \mid x)$, where $x \in \mathbb{R}^d$ is the input and $y \in \mathbb{R}$ is the target variable. The KCDE-F method uses kernel methods and random Fourier features to approximate this conditional density efficiently).The mathematical details of the KCDE-F Algorithm are expressed as follows:

i. Kernel Trick and Conditional Density Estimation

The conditional density estimation using kernels can be expressed as $p(\, y \mid x\,) = \sum_{i=1}^{n} w_i(x) K(y, y_i)$ (6)

where $K(\cdot,\cdot)$ is a positive definite kernel function, $\{y_i\}_{i=1}^{n}$ are the target variables from the training set, and $w_i(x)$ are weights dependent on the input x (Rosenblatt, 1969).

ii. Random Fourier Features

To approximate the kernel $K(y, y')$, KCDE-F uses random Fourier features as proposed by Rahimi and Recht (2007). According to Bochner's theorem, any shift-invariant kernel can be approximated as:

$K(y, y') \approx \phi(y)^{\top}\phi(y')$,where $\phi(y) = \sqrt{\frac{2}{D}}[\cos(\omega_1^{\top} y + b_1), \ldots, \cos(\omega_D^{\top} y + b_D)]$, with $\omega_i \sim \mathcal{N}(0, \Sigma)$ and $b_i \sim$ Uniform $(0, 2\pi)$.

iii. Weight Estimation

The weights $w_i(x)$ are determined by solving a regularized least squares problem to balance fit and smoothness:

$$\min_{w(x)} \sum_{i=1}^{n} \left\| \emptyset(y_i) - \sum_{j=1}^{n} w_i(x)\emptyset(y_i) \right\|^2 + \lambda \|w(x)\|^2$$

where λ is the regularization parameter controlling the trade-off between bias and variance (Rifkin & Lippert, 2007).

iv. Conditional Density Estimation

The conditional density is estimated as:

$$\hat{p}(y \mid x) = \phi(y)^{\top} W(x) \Phi_Y$$

where Φ_Y is the matrix of Fourier features for the target variable, and $W(x)$represents the estimated weights for input x.

Pseudo Code for of KCDE-F

Input: Select a kernel function K.

Generate random Fourier features $\phi(y)$ using w and b.

Map each target y_i to its Fourier feature representation $\phi(y_i)$.

Weight Estimation:

Estimate $w(x)$ for each input x by solving the regularized least squares problem.

Conditional Density Estimation:

For a given x and$y$, compute $\hat{p}(y \mid x)$ using the estimated weights and Fourier features.

Output:

Return the estimated conditional density $\hat{p}(\, y \mid x\,)$.

3.3 Development of Classification the Program

The classifier was implemented in the Python 3.10 programming language. Its simplicity and the presence of libraries specially fitted for data science tasks enormously facilitated the development process as a whole. Python was chosen because it handles the whole development process, from data manipulation with Pandas to numerical computations with NumPy, machine learning with Scikit-learn, and visualization with Matplotlib - out-of-the-box.

3.3.1 Installing Libraries in Python

The program depends on various libraries in Python, each for various reasons: data manipulation, visualization, and machine learning. I installed the following (using the “pip install numpy pandas matplotlib scikit-learn” command) to set up my environment:

i.NumPy: For numerical computations, this library was used, as it allowed operations to be done with multi-dimensional arrays efficiently. This library was actually the base of almost all data processing and manipulation.

ii. Pandas: This will be the backbone library in this project, since cleaning, preprocessing, and structuring of the CPI dataset will be done with its use.

iii. Matplotlib: This will be used to visualize the data and results of the classification. It plots the trends of CPI and highlights the detected change points on the graph.

iv. Scikit-learn: It is a more specialized machine learning library that had been used in the implementation of the KCDE-F model. Tools from this library were used for density estimation, random forests, and model evaluation.

3.3.2 Program Development

In developing the program, the specific steps were carried out:

i. Dataset Loading and Preprocessing: The dataset containing the values of CPI is loaded into a pandas DataFrame, which is handy for manipulation. After converting time values into numerical and matching them to the CPI value for analysis:

ii.KCDE: We applied the KCDE technique using the Kernel Density module from scikit-learn by instantiating a Gaussian kernel with an appropriate bandwidth to estimate conditional densities of CPI values over time. The model helped detect anomalies or significant changes in the CPI trends.

iii.Random Forest Integration:

A random forest regressor was constructed using the Random Forest Regressor class from scikit-learn. Such an ensemble method will make sure that any subset of data will have a robust estimation of density. This will also increase the sensitivity toward temporal dependencies in the trends of the CPI.

iv. Change Point Detection: Changes were observed to identify change points based on fluctuations in density estimations. Major deviations in log-density values were marked as possible change points.

v. Visualization: A point plot of the CPI time series trend was provided using matplotlib; then, markers in the figure, showing the period that there is considerable variation, pointed out the different change points of this classification program output. This gave a good insight into the representation of the results.

4. Results

4.1 Test Result of Data Classification Program

From the resultant graph obtained from the classification program in Figure 1, it can be seen that the CPI graph from January 2019 to August 2023 is generally upward, with several points reflecting change. The points indicated in “red” identify the change points within the time-series data. These changes have resulted from economic events and implemented policies in Nigeria within this period. This is in consonance with the graph shown in Figure 2, obtained from the National Bureau of Statistics via Statista (2024) – an online portal for market data, market research and market studies.

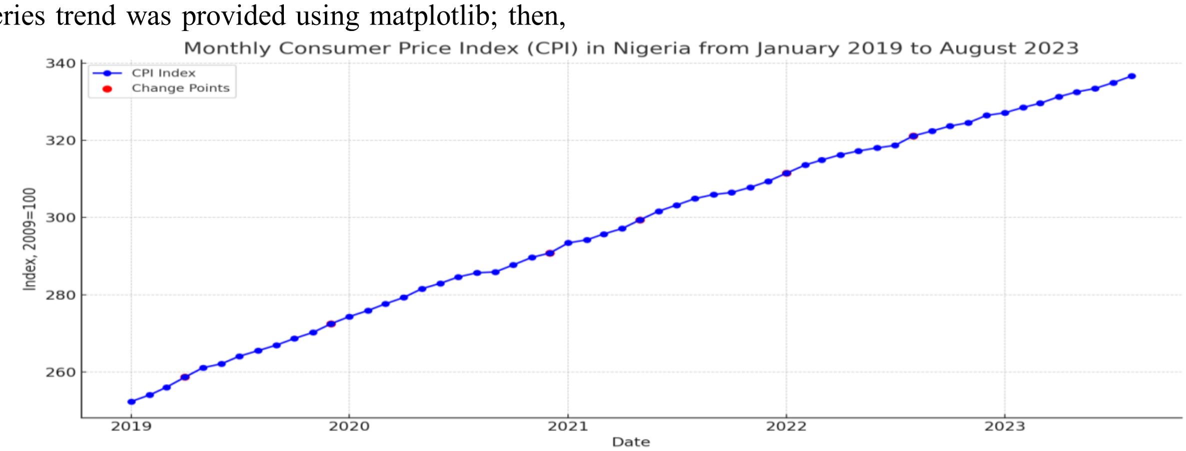

Figure 1: CPI graph obtained as result of the Data Classification Program

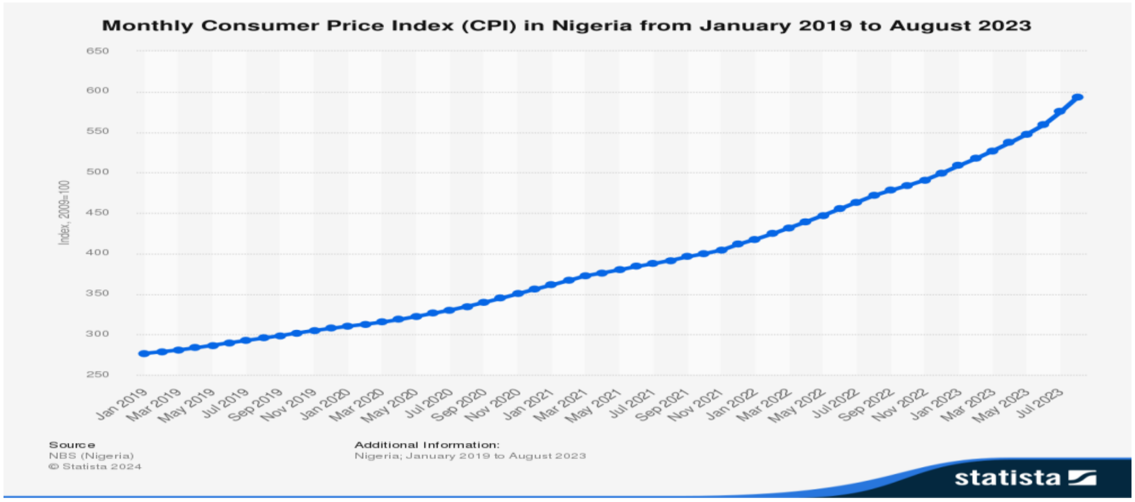

Figure 2: CPI graph from National Bureau of Statistics for January 2019 to August 2023 (Statista, 2024)

A brief insight into the cause and effect resulting in the change points are as follows:
i. Pre-Pandemic Stability (2019): Generally, the upward trend in the economy-wide CPI for 2019 reflected a period of relative economic stability in Nigeria as sustained by reasonable rates of inflation. This was because there were generally stable oil prices and agricultural output during this period. The Central Bank of Nigeria's 2019 Annual Report states that monetary policy measures implemented to support the naira and limit liquidity have kept inflation within manageable bounds (Central Bank of Nigeria, 2019).
ii. COVID-19 Pandemic in 2020: At the early part of the year 2020 making the beginning of the COVID-19 pandemic occurred, a notable change occurred. At that time, there is a sharp rise in the increase of CPI, which can be explained by disrupted supply chains, decreased oil revenues, and lockdowns by the government. The Nigeria government responded with Economic Sustainability Plan (ESP) in 2020 to cushion the impact but the pressure of inflation was not abated because of increased costs of goods imported into the country and disruptions to food supply (Federal Government of Nigeria, 2020).
iii. Post-Pandemic Recovery and 2021 Currency Devaluation: Another turning point was the middle of 2021. The post-pandemic economic recovery that began during this period was characterized by increased consumer demand and currency devaluation. One of the main issues that led to imported inflation was the depreciation of the naira. According to the 2021 Financial Stability Report, the CBN has been trying to manage foreign exchange rates and the fluctuations in the price of commodities on the global market (Central Bank of Nigeria, 2021).
iv. Fuel Subsidy Removal and Food Inflation (2022): In the year 2022, the inflation rate continued to witness another upward structural shift. This is in tandem with the rise in transportation and production costs due to the removal of fuel subsidies. Besides, food inflation remained high on account of sustained insecurity in food-producing areas.The National Bureau of Statistics identified these factors as the main drivers of inflation in its 2022 Inflation Report (National Bureau of Statistics, 2022).
v. Monetary Policy Tightening, 2023: By mid-2023, the trend in the CPI started becoming stable. This period reflects the impact of monetary tightening by the CBN through increasing the Monetary Policy Rate, MPR, as inflation continued to be above the targeted limit. In this respect, the 2023 communique of the Monetary Policy Committee of the CBN reiterates that the Committee is committed to the attainment of price and economic growth (Central Bank of Nigeria, 2023).

5. Conclusion

The study proposes a three-step nonparametric change point detection method which is an advancement of the common two-step approach.

Our methodology embeds the principles of Kernel Conditional Density Estimation with Fourier features in a robust manner for the determination of structural shifts in time-series data. First, the preprocessing of the data is performed to set the correct ground for good detection by assuring smoothness and removing noise. Further in sequence comes the step that includes the approach called KCDE-F, which estimates conditional density, allowing the precise identification of points of a putative change. The machine-learning classifier refines the detected points to increase sensitivity and specificity. We applied this algorithm to the Nigerian inflation data for 2019-2023. Results include critical change points that offer useful insights into how the dynamics of inflation respond to economic policies and external shocks. The approach provides a strong tool for economists but finds broad applicability across domains requiring change point detection. We hereby confirm the development of a unique three-step methodology that brings together statistical strength and machine learning within an overarching package of complex time-series analysis. This study opens a pathway to much subtler understandings and active manipulations of economic and financial tendencies.

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