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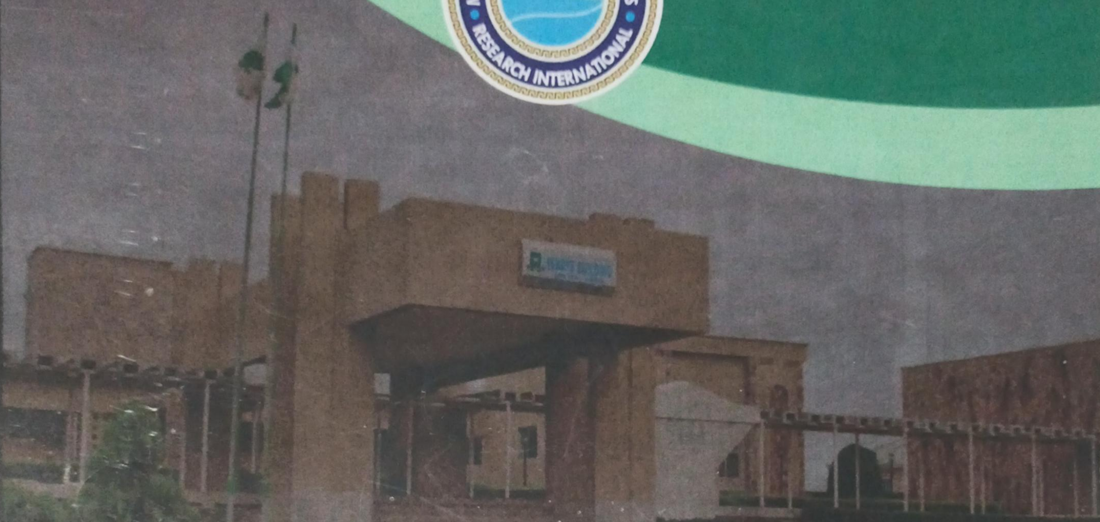

PHYSICAL/VIRTUAL PRESENTATION

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APPLICATION OF SOME FORECASTING MODEL FOR PRIDICTING PRICES ON AGRICULTURAL COMMONDITIES IN FEDERAL CAPITAL TERRITORY ABUJA

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ABSTRACT

This study evaluates the performance of various forecasting models in predicting the prices of agricultural commodities in the Federal Capital Territory (FCT). The aim is to identify the most effective model for forecasting food prices and to analyze trends over a seven-year period. Key forecasting models applied include Exponential Moving Average (EMA), Seasonal Autoregressive Integrated Moving Average (SARIMA), Exponential Smoothing, and Support Vector Regression (SVR). Model performance was assessed using average Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Results showed that the Exponential Moving Average model outperformed others, with the lowest average MAE (94.05), MSE (66895.17), and RMSE (219.04). The study also identified consistent trends in food prices over the forecasted five-year period (2024–2028) for key commodities such as rice, maize, soybeans, yam, and Garri. The forecasted price of milled rice remained stable at 929.21 Naira, while yam maintained a consistent price of 3320.59 Naira throughout the period. The findings suggest that the Exponential Moving Average model is a robust tool for predicting agricultural commodity prices in the FCT, enabling better decision-making and resource allocation in the sector.

INTRODUCTION

Food is a fundamental aspect of human life, providing the necessary nutrients to sustain health and well-being. It encompasses a wide variety of substances from plant and animal origins, each contributing uniquely to our dietary needs. Beyond its nutritional value, food is deeply embedded in cultural, social, economic, and environmental contexts, making it a vital component of our daily lives. The essential role of food in human life is well acknowledged. To sustain health and obtain sufficient energy for daily activities, access to food that meets quality and quantity standards is necessary.

As essential consumption goods, food has a continuous demand that increases in line with the world's population growth. Furthermore, this food must be affordable, as cost significantly influences people's ability to obtain it. There are different types of food, this study will consider cereals, vegetables, legumes, tubers, fruits, proteins and oil. Cereals, also known as grains, are edible seeds or fruits of grass species that are cultivated for food. They are a staple food for a large portion of the world's population due to their high energy content and nutritional value. Cereals are a primary source of carbohydrates and provide essential nutrients, including proteins, vitamins, minerals, and dietary fiber. Some of the examples are rice, maize, guinea corn, millet and so on. Vegetables are parts of plants that are consumed by humans as food. They are a vital component of a balanced diet, offering a wide range of nutrients, including vitamins, minerals, fiber, and antioxidants. Vegetables come in various forms, including leaves, stems, roots, tubers, flowers, seeds, and fruits. They can be eaten raw, cooked, or processed in numerous ways. Legumes are a category of plants in the Fabaceae family known for their seed-bearing pods. These seeds, also called pulses when dried, are highly nutritious and serve as a major source of protein, fiber, and various vitamins and minerals. Legumes are a staple food in many cultures around the world and play a crucial role in both human nutrition and agriculture. Some of the examples are; cowpea, melon, groundnut, soyabeans and so on. Tuber are a type of plant structure used for storing nutrients, often rich in carbohydrates. They are typically grown underground and serve as an important food source for both humans and animals. Tubers include some of the most widely consumed staple foods globally such as potatoes and cassava.

Fruits are the mature ovary of a flowering plant, typically containing seeds. They are usually sweet or tart and can be eaten raw or cooked. Fruits are an essential part of a balanced diet due to their rich nutrient content, including vitamins, minerals, fiber, and antioxidants. Examples are, oranges, mango, pawpaw, pineapple and so on. Meat and fish are primary sources of animal protein in the human diet, providing essential nutrients necessary for growth, development, and overall health. We have beef, chicken, turkey, smoked fish, ice fish, dry fish and so on. Oils are liquid fats derived from plants, nuts, seeds, or animal sources that are used for cooking, flavoring, and in some cases, as dietary supplements. They play a crucial role in culinary practices and nutrition. We have groundnut oil, palm oil, shea butter and so on.

Food and nutrition security are the fundamental challenges to human welfare and economic growth in Africa (Benson, 2004). Lack of access to food influences food intake and consequently impact on the health and nutritional status of households (Beyene, 2023). Many Nigerians are finding life increasingly challenging, struggling to secure the essential needs of food, clothing, and shelter. The rises in prices witnessed between June 2020 and June 2021 alone, according to the World Bank, "could push another six million Nigerians into poverty with urban areas disproportionately affected" (Olanrewaju, 2021). The aim will be achieved using the following objectives; To examine the estimate of food prices in FCT for each of the food under consideration using the best model and Identify the patterns (trend) in food pricing for the period of 7 years

MATERIALS AND METHODS

Materials

A combination of software tools will be employed for data preparation, statistical analysis, and modeling. For the initial stage, **Microsoft Excel 2016** will be used to organize the raw data. After the data preparation in Excel, the dataset will be imported into **Python 3** through **Jupyter Notebook** with the ipykernel environment. Python will be used for detailed analysis. The statistical models used are **Exponential Moving Average (EMA), The Seasonal Autoregressive Integrated Moving Average Model (SARIMA), Exponential Smoothing and Support Vector Regression (SVR)**

Models

Exponential Moving Average (EMA)

A moving average is a statistical technique used to smooth out short-term fluctuations and highlight longer-term trends or cycles in data. It's widely used in time series analysis to analyze historical data, make forecasts, and identify trends in various fields, including finance, economics, and meteorology. In the context of food prices, moving averages help to understand and predict price trends over time.

Exponential Moving Average (EMA) is a type of moving average that places a greater weight and significance on the most recent data points, (Maverick, 2024).

$$EM\,A_t = \alpha \times P_t + (1-\alpha) \times EMA_{t-1} \quad (2.1)$$

where:

$EM\,A_t$= the Exponential Moving Average at time t.

α = the smoothing factor.

P_t = the price at time t.

EMA_{t-1} = the EMA of the previous period.

The smoothing factor α is typically calculated as:

$$A = \frac{2}{n+1}$$

where n is the number of periods over which the EMA is calculated.

The Seasonal Autoregressive Integrated Moving Average Model (SARIMA)

SARIMA models are widely used in various fields such as economics, finance, weather forecasting, and any domain where data exhibits seasonal patterns. By incorporating seasonality into the ARIMA framework, SARIMA provides a more accurate and robust method for forecasting seasonal time series data, (Naden and Etuk, 2017).

$$(1-\emptyset_1 \mathrm{B})(1-\Phi_1 \mathrm{B}^s)(1-\mathrm{B})(1-\mathrm{B}^s)y_t = (1+\theta_1 \mathrm{B})(1+\Theta_1 \mathrm{B}^s)w_t \quad (2.2)$$

Where:

$(1-\emptyset_1 \mathrm{B})$ = Autoregressive (AR)

$(1-\Phi_1 \mathrm{B}^s)$ = Seasonal Autoregressive (SAR)

$(1-\mathrm{B})$ = Non-seasonal Autoregressive

$(1-\mathrm{B}^s)$= Seasonal differencing component

y_t = observed time series at time (t),

B = shift operator, representing the lag operator (i.e., $B\,y_t = y_{t-1}$)

ϕ_1= non-seasonal autoregressive coefficient,

Φ_1= seasonal autoregressive coefficient,

θ_1= non-seasonal moving average coefficient,

Θ_1= seasonal moving average coefficient,
s = seasonal period,
ε_t = white noise error term at time t.

Exponential Smoothening

Triple Exponential Smoothing (Holt-Winters' Method): Triple exponential smoothing, also known as Holt-Winters' method, extends double exponential smoothing to account for seasonality in addition to trends. It involves three components: level, trend, and seasonality, (Mayaki *et al.*, 2023)

$$Y_{t+m} = L_t + mT_t + S_{t-m+k} \quad (2.3)$$

Where:

$$L_t = \alpha(Y_t - S_{t-m}) + (1-\alpha)(L_{t-1} + T_{t-1})$$
$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$
$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-m}$$

Where:
Y_{t+m} = the forecast for time $t + m$
L_t = the level at time t
T_t = the trend at time t,
S_t = the seasonal component at time t,
Y_t = the observed value at time t,
α, β, γ ($0 < \alpha, \beta, \gamma < 1$) are smoothing parameters for the level, trend, and seasonal components, respectively,
m is the seasonal period,
k is an integer such that $1 \le k \le m$

Support Vector Regression (SVR)

This an extension of Support Vector Machines (SVM) that is used for regression tasks rather than classification (Meesad and Rasel, 2013).

$$\min_{w,b,\xi,\xi^*} \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} (\xi_1 + \xi_1^*) \quad (2.4)$$

$\| w \|^2$represents the flatness of the function, $\xi_1^* and \xi_1$ are slack variables that allow some errors to be tolerated, and C is a regularization parameter that balances the trade-off between model complexity and the amount up to which deviations larger than ϵ are tolerated.

Constraints:

$$y_i - (w^T x_i + b) \le \epsilon + \xi_i$$
$$(w^T x_i + b) - y_i \le \epsilon + \xi_i^* \quad (2.5)$$
$$\xi_i, \xi_i^* \ge 0$$

These constraints ensure that the error for each data point is within the ϵ\epsilone margin, with slack variables allowing for some points to lie outside this margin.

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Evaluation of Model

Mean Absolute Eror (MAE)

It is a metric used to measure the average magnitude of errors between predicted values and actual values, (Mayaki *et al.*, 2023). MAE is calculated as the average of the absolute differences between predicted values $\hat{y}_i$ and actual values y_i across all observations i (Hodson, 2022)

$$MAE = \ln \sum_{i=1}^{n} |\hat{y}_i - y_i| \tag{2.6}$$

where:
n = number of observations,
$\hat{y}_i$ = predicted value,
y_i = actual value,
$|\hat{y}_i - y_i|$ = absolute difference between the predicted and actual values.

The Root Mean Squared Error (RMSE)

The Root Mean Squared Error (RMSE) is the square root of the average squared difference between predicted and actual values. It quantifies the magnitude of prediction error (Hodson, 2022)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(y_i - \hat{y}_i)^2} \tag{2.7}$$

where:
y_i is the actual value at time i
$\hat{y}_i$ is the predicted value at time i
n is the number of observations.

Mean Square Error (MSE)

Is a common measure used to evaluate the accuracy of a time series model. It quantifies the average squared difference between the actual values and the predicted values (Frost, 2024)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2.8}$$

where:
y_i is the actual value at time i,
$\hat{y}_i$ is the predicted value at time i
n is the number of observations.
The model with smaller MAE, RMSE and MSE values indicate better predictive accuracy.

Data Source and Description

Secondary data will be used for this research work, which will be obtained from Agricultural & Development Secretariate (ARDS) FCTA. The data that will be gotten will contain retail prices of different food items (cereals, vegetables, legumes, tuber, fruits, proteins and oils) between January 2015- December 2019 and January 2021- December 2023.

RESULTS AND DISCUSSIONS

Model Performance

Table 3.1: Mean Absolute Error

	Exponential Moving Average	SARIMA	Exponential Smoothing	SVR
Milled Rice	87.42303	158.6282	216.9298	149.5804
Maize	58.81743	122.9795	115.5801	86.62347

Soyabean	**45.28047**	102.4026	110.7182	92.4843
Yam Tuber	**182.7907**	328.8454	369.098	666.6924
Garri (White)	**25.72889**	61.34768	57.40367	46.34376
Sweet Potato	**72.07754**	150.277	161.5553	166.7462
Pepper	**52.15247**	101.0349	106.2126	121.5638
Tomatoes	**19.25769**	48.24101	46.75014	42.16556
Orange	**226.1461**	393.0804	358.0131	353.2081
Beef	**95.47907**	203.4819	202.6208	195.9925
Ice Fish	**142.5112**	282.123	277.6753	413.1552
Palm Oil	**102.3458**	200.7728	257.0034	172.2511
G/nut Oil	**112.6549**	253.0344	252.4608	178.5095

EMA consistently delivers the lowest MAE for most commodities, indicating better short-term forecasting accuracy. SARIMA and Exponential Smoothing tend to have higher errors, particularly for volatile commodities like Yam tubers and Pepper. SVR performs relatively well for some commodities like milled rice and Garri, but struggles with high-volatility items like Yam tubers and Ice Fish.

Table 3.2: Root Mean Squared Error

	Exponential Moving Average	SARIMA	Exponential Smoothing	SVR
Milled Rice	**290.4177**	516.4213	535.804	574.3001
Maize	**170.8298**	309.0196	306.2261	300.4117
Soyabean	**101.9848**	194.523	194.4424	204.0633
Yam Tuber	**329.5861**	596.8351	582.5751	933.8882
Garri (White)	**55.11516**	110.8837	103.3641	105.8477
Sweet Potato	**167.0994**	329.1168	320.9634	323.3688
Pepper	**91.88024**	176.653	173.3082	197.1009
Tomatoes	**59.50247**	114.0358	112.1848	120.756
Orange	**572.551**	1023.109	991.0732	1007.815
Beef	**204.2541**	379.6924	397.5764	390.2762
Ice Fish	**208.5257**	409.7966	392.8022	503.9897
Palm Oil	**255.2195**	488.8755	495.4146	507.0674
G/nut Oil	**340.5691**	634.1073	603.7247	610.3232

EMA achieves the lowest RMSE for most commodities, suggesting it is effective for reducing large errors in predictions. SARIMA shows higher RMSE values for seasonal and volatile commodities such as yam tubers and orange. SVR has the highest RMSE for certain volatile commodities, such as ice fish, indicating sensitivity to extreme fluctuations.

Table 3.3: Mean Square Error

	Exponential Moving Average	SARIMA	Exponential Smoothing	SVR
Milled Rice	**84342.45**	266690.9	287086	329820.6
Maize	**29182.83**	95493.13	93774.42	90247.22
Soyabean	**10400.9**	37839.19	37807.85	41641.84
Yam Tuber	**108627**	356212.1	339393.8	872147.3
Garri (White)	**3037.681**	12295.2	10684.15	11203.73
Sweet Potato	**27922.21**	108317.9	103017.5	104567.4
Pepper	**8441.978**	31206.28	30035.72	38848.76

Tomatoes	**3540.544**	13004.17	12585.44	14582.01
Orange	**327814.6**	1046753	982226.1	1015692
Beef	**41719.75**	144166.3	158067	152315.5
Ice Fish	**43482.96**	167933.3	154293.6	254005.7
Palm Oil	**65136.99**	238999.3	245435.6	257117.4
G/nut Oil	**115987.3**	402092	364483.5	372494.4

EMA dominates in minimizing MSE, showcasing its robustness in short-term prediction accuracy. SARIMA and Exponential Smoothing exhibit larger MSE values for highly seasonal and volatile commodities. SVR has significantly higher MSE for commodities like yam tubers and ice fish, further underscoring its limitations in handling volatility.

Table 3.4: Average model comparison

	Average MAE	Average MSE	Average RMSE
Exponential Moving Average	**94.05117**	**66895.17**	**219.0412**
SARIMA	185.096	224692.5	406.39
Exponential Smoothing	194.7709	216837.7	400.7276
SVR	206.5628	273437.2	444.5545

Exponential Moving Average (EMA) has the lowest average MAE (94.05117), indicating it produces the most accurate predictions overall. SARIMA and Exponential Smoothing follow, with higher average errors (185.096 and 194.7709, respectively). SVR has the highest average MAE (206.5628), suggesting less precise predictions compared to the other models.

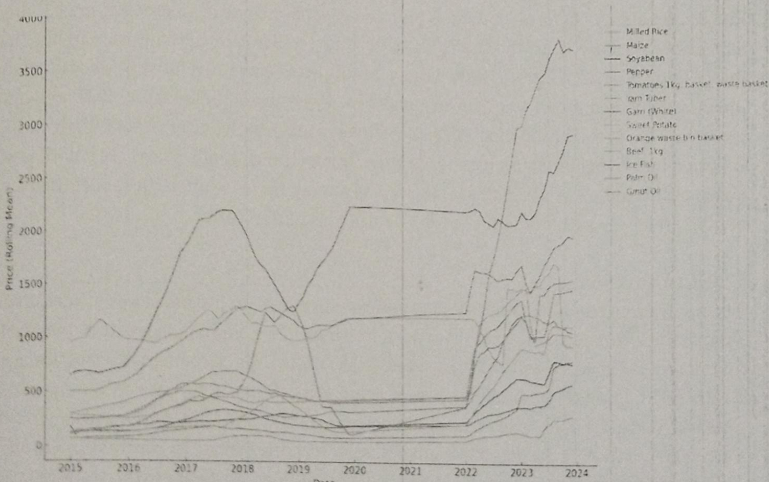

Figure I: 12-Month Rolling Average (Trend)

Tomatoes (Red line) Shows extreme price fluctuations between 2017–2019. Stabilizes briefly but spikes again post-2021, reflecting potential supply chain disruptions or seasonal dependency. Milled Rice (Orange line) demonstrates steady growth in price, particularly after 2021. This could indicate long-term demand growth or challenges in production. Maize (Yellow line), experiences gradual price increases over time, with a significant rise after 2021. Indicates its consistent role as a staple commodity. Ice Fish (Bright Pink line) among the most volatile commodities. Peaks sharply in 2018 and again in 2022-2023, possibly due to seasonal fishing cycles or external factors like fuel or transportation costs. Palm Oil (Greenish-blue line) prices steadily climb post-2021, highlighting its growing demand in food production and industrial use. The increase may also reflect global market trends such as reduced palm oil exports from major producers. Groundnut Oil (Blue line) shows steady but slower growth compared to Palm Oil. Prices increase more significantly in 2022-2023, potentially tied to overall market inflation. Sweet Potato (Light green line) has steady growth with a marked increase post-2021. Indicates its stable role as a staple food commodity with fewer external market pressures. Soyabeans (Yellow-Green Line) show a consistent upward trajectory, with a significant price spike after 2021. From 2015 to 2021, prices grew gradually, reflecting stable demand and supply conditions. Post-2021, the prices surged sharply, possibly due to global agricultural disruptions, increased demand, or rising production costs.

Pepper (Pink Line) prices exhibit periodic fluctuations but a general upward trend, particularly after 2021. Pre-2021 prices are relatively stable, with seasonal variations and post-2021 has a sharp price increase likely due to supply shortages, inflationary pressures, or heightened demand for spices. Yam Tuber (Light Blue Line) prices show steady growth with significant volatility before 2020 and a sharp post-2021 increase. Fluctuations occur before 2020 likely due to seasonal harvests or production challenges and prices escalate sharply after 2021 reflecting economic or agricultural supply chain disruptions. Garri (White) (Bright Green Line) prices have a relatively smooth, steady upward trend compared to other commodities. Prices are stable before 2021, reflecting consistent cassava production. Prices increase moderately after 2021, likely due to inflation and rising production costs. Orange (Dark Orange Line) prices are volatile, with sharp peaks and troughs pre-2021, followed by a steep increase after 2021. Beef (Red Line) exhibit steady growth over time, with a sharper rise after 2021.

CONCLUSIONS

The analysis on the application of some forecasting model for predict prices of agricultural commodities in Federal Capital Territory in Abuja. This finding shows that among the four forecasting methods that were used (EMA, SARIMA, Exponential smoothing and SVR), EMA has the least average, indicating it performs well on average across the dataset. SARIMA and Exponential Smoothing follow EMA in performance, proving particularly effective for forecasting seasonally varying items. In contrast, SVR shows higher average errors, indicating it may be less suitable for tasks with strong seasonal patterns. Foods like Milled Rice, Maize, and Palm Oil show a steady upward trend, likely due to inflation or higher production costs. Yam Tuber, Garri, and Sweet Potatoes fluctuate seasonally with harvest cycles. Tomatoes and Ice Fish experience sharp fluctuations tied to supply and demand shifts, while Beef and Groundnut Oil remain relatively stable, reflecting consistent demand or production stability.

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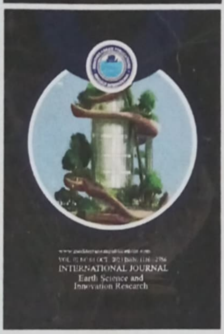

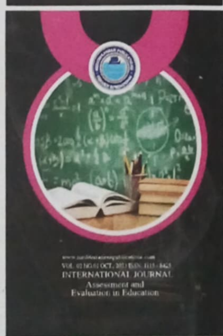

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