

**PROJECT TITLE**

**BY**

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**A Project submitted to the Department of Mathematical Sciences, Faculty of Natural, Applied and Health Sciences in partial fulfillment of the requirements for the award of Bachelor of Science (B.Sc.) Degree in Computer Science.**

**July, 2024**

DECLARATION

I hereby declare that this Project was written by me and is a correct record of my research work. It has not been presented in any previous application for any degree of this or any other University. All citations and sources of information are acknowledged using references.

…………………………

SURNAME, FIRSTNAME, INITIALS.

Date:…………………….

CERTIFICATION

I hereby certify that this project work entitled “Unified Code for Collocation Multistep Methods in Solving Systems of Ordinary Differential Equations” was carried out by OKWHAROBO Solomon Monday, with a matric number AUL/SCI/20/00605, under the supervision of Supervisor and has not been submitted in part or full to this university or other institutions for the award of a degree.

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ABSTRACT

*This section presents the abstract of your project. Note that it must be in italics*

ABBREVIATIONS

AI – Artificial Intelligence

ML – Machine Learning

R2 – R-Squared

DEDICATION

This Project is dedicated to God the Father, Son, and Holy Ghost for the wisdom, mercy, and favor shown to me throughout the program and also to my beloved parents for their unwavering love and care.

ACKNOWLEDGMENTS

I express my heartfelt gratitude to the Almighty, who has been my source of strength throughout this course, particularly during the research work.

I would like to extend my sincere and deepest appreciation to my supervisor,

I would also like to express my heartfelt appreciation to my co-supervisor.

I would like to express my sincere gratitude and appreciation to Dr. D.D. Aleburu the HOD, for her valuable contributions and insightful suggestions. I am also thankful to all the lecturers in the Department of Mathematical Sciences for their dedication, time, and guidance during my seminar presentations.

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# 

**INTRODUCTION**

## 1.1 Background to the Study

Food is an essential component of human existence, fundamental to the survival and well-being of every individual. It stands alongside shelter, clothing, and financial stability as one of the core necessities of life (Lorena and Juan, 2021). However, without adequate food, the quality of life deteriorates significantly. Access to nutritious and sufficient food is directly linked to overall health, productivity, and happiness. The phrase "good food, good mood" (Jess and Chloe, 2024) encapsulates proper nutrition's profound impact on mental and emotional well-being. Food transcends mere sustenance; it is crucial for maintaining physical health, supporting cognitive functions, and fostering social bonds.

Food prices play a pivotal role in determining the accessibility and affordability of nutritious food. In many parts of the world, including Nigeria, fluctuations in food prices can have severe implications for food security. High food prices can limit the ability of households to purchase a diverse and balanced diet, leading to malnutrition and related health problems. Conversely, affordable food prices can enhance food security, allowing families to meet their dietary needs and improve their quality of life. Therefore, understanding and predicting food prices is vital for ensuring that all population segments can access nutritious food (Patrick and William, 2021).

Several factors influence food prices in Nigeria, contributing to their volatility and unpredictability. These factors include: Nigeria's rapidly growing population and increasing urbanization drive higher demand for food. Urban areas, in particular, experience shifts in dietary patterns, with a growing preference for processed and imported foods, which can affect local food prices (Ivica et al, 2023). Climate change impacts agricultural productivity through changes in rainfall patterns, increased frequency of extreme weather events, and shifts in growing seasons. Environmental degradation, such as soil erosion and deforestation, further exacerbates these challenges, leading to reduced crop yields and higher food prices (Muhammad et al, 2022).

Economic instability, inflation, and poverty levels in Nigeria influence food prices (P. A Okuneye, 2005). Limited access to credit and financial resources can hinder farmers' ability to invest in agricultural inputs and technologies, affecting productivity and, consequently, food prices. Inefficiencies in the food supply chain, including poor infrastructure, inadequate storage facilities, and transportation challenges, contribute to food price volatility. Post-harvest losses due to these inefficiencies also affect the availability and cost of food.

Given the significant impact of food prices on food security and overall well-being, there is a pressing need to predict and forecast food prices accurately. Predictive models can help policymakers, farmers, and stakeholders make informed decisions to stabilize food prices and ensure a steady supply of affordable and nutritious food (L. Chitondo et al, 2024). Forecasting food prices can aid Governments and agricultural stakeholders in using food price forecasts to develop strategies and policies that mitigate the adverse effects of price volatility. Accurate predictions can help stabilize markets by informing supply chain management and reducing the uncertainty that drives price spikes. Farmers and agribusinesses can optimize the allocation of resources such as seeds, fertilizers, and labour based on anticipated price trends. Forecasting can help protect consumers from sudden price hikes, ensuring that food remains affordable for all segments of society.

Historically, various methods have been used to predict food prices, often based on seasonal patterns, historical data, and market observations. Some of these methods include:

Seasonal Trends: Food prices are often influenced by seasonal changes. For example, prices may rise during festive seasons or religious fasting periods due to increased demand (Eline D'Haene, 2021). While this approach provides some insight, it lacks the precision needed to account for unexpected variables.

Historical Data Analysis: Analyzing historical price trends can offer some predictive value (Piyush Mishra, 2021). However, this method is limited by its inability to account for sudden changes in supply and demand dynamics.

Market Observations: Farmers and traders have traditionally relied on market observations and personal experience to predict price changes (Bob Baulch et al, 2020). While valuable, these methods are inherently subjective and lack the robustness needed for accurate forecasting. The limitations of these traditional methods underscore the need for more sophisticated approaches to forecasting food prices.

Machine Learning (ML) presents a promising solution to the challenges of food price forecasting. ML leverages large datasets, advanced algorithms, and computational power to identify patterns and make accurate predictions. The application of ML in food price forecasting offers several advantages as ML models can integrate diverse data sources, including historical prices, weather patterns, market trends, and socioeconomic indicators, providing a comprehensive analysis of factors influencing food prices (R. Kler et al, 2022). ML systems can handle vast amounts of data, making them suitable for large-scale applications across different regions and agricultural products.

Advanced algorithms can detect complex patterns and relationships in the data that traditional methods might overlook. This capability enhances the accuracy and reliability of price forecasts. ML models can process data in real-time, offering up-to-date predictions that help stakeholders respond promptly to emerging trends and market changes (Sultan Saeed et al, 2024).

The integration of ML in food price forecasting is essential for improved accuracy as ML algorithms can provide more accurate and reliable forecasts than traditional methods, helping to stabilize food prices and improve food security. By offering precise and timely predictions, ML empowers policymakers, farmers, and businesses to make informed decisions that optimize food production and distribution. Accurate forecasts enable better resource allocation, reducing waste and increasing the efficiency of agricultural practices and supply chains. ML models can adapt to changing conditions and continuously improve their predictions as more data becomes available (Adel N. Toosi, et al, 2019).

Ensuring food security in Nigeria requires innovative approaches to address the complexities of food production, distribution, and consumption. Machine learning offers a powerful tool for predicting food prices, providing valuable insights that can enhance agricultural practices, optimize supply chains, and improve the overall food system. By leveraging the capabilities of ML, Nigeria can move towards a more stable and secure food future.

## 1.2 Research Motivation

As one of Africa's most populous nations, Nigeria faces significant challenges in ensuring an adequate and reliable food supply for its growing population. With population growth projected to reach 400 million by 2050 (UNFPA Nigeria, 2023), coupled with rapid urbanization and shifting dietary patterns, the demand for food is escalating, placing unprecedented strain on agricultural systems and food supply chains.

Moreover, Nigeria struggles with myriad compounding factors that worsen food insecurity, including climate change-induced disruptions, environmental degradation, and socio-economic constraints (Kelechi Ani et al, 2022). Erratic rainfall patterns, prolonged droughts, and extreme weather events jeopardize crop yields and livestock productivity, while deforestation, soil erosion, and pollution undermine agroecosystem resilience. Additionally, poverty, inadequate infrastructure, and limited access to credit further exacerbate the vulnerability of marginalized communities, impeding their ability to attain food self-sufficiency.

Despite Nigeria's abundant agricultural resources, the country faces persistent challenges in ensuring stability and affordability in food prices. Fluctuations in food prices can have profound impacts on consumer purchasing power, food security, and overall economic stability (Raheel Suleman et al, 2021). Therefore, there is a critical need to develop accurate and reliable models for predicting food prices, enabling policymakers, businesses, and consumers to make informed decisions and mitigate the adverse effects of price volatility.

In this context, the application of modern technologies such as machine learning (ML) presents a compelling solution to address the multifaceted challenges plaguing Nigeria's food system. By harnessing vast datasets, advanced algorithms, and computational power, ML offer unprecedented opportunities to enhance agricultural productivity, optimize resource allocation, and mitigate risks across the food value chain. Unlocking the transformative potential of ML technologies to revolutionize agricultural practices, improve food production, distribution, and consumption, and ultimately, ensure a sustainable and food-secure future for Nigeria.

The goal is to investigate how machine learning might be used to address important problems with Nigeria's food security, identify barriers to adoption, and propose actionable recommendations to harness the full potential of modern technologies in transforming the agricultural landscape. By shedding light on the role of technology in bolstering food security, with the hope of inspiring stakeholders across sectors to prioritize investments in digital innovation, foster collaboration, and catalyze positive change towards a hunger-free Nigeria.

This project aims to address the following key problems:

Unpredictability of Food Prices: The lack of reliable forecasting models makes it difficult for stakeholders to anticipate changes in food prices, leading to market uncertainties, supply chain disruptions, and inefficient resource allocation. By developing robust ML-based prediction models, this project seeks to provide timely insights into future price trends, enabling stakeholders to proactively manage risks and optimize decision-making processes.

Regional Disparities in Price Dynamics: Nigeria's diverse geographical and socio-economic landscape gives rise to significant regional variations in food prices, influenced by factors such as transportation costs, market infrastructure, and local demand-supply dynamics. This project aims to capture and analyze spatial patterns in food price movements across different states in Nigeria, facilitating targeted interventions and policy interventions to address disparities and enhance market efficiency.

Impact of External Factors on Food Prices: Food price dynamics in Nigeria are influenced by a myriad of external factors, including macroeconomic indicators, weather patterns, global market trends, and government policies. Understanding the complex interplay of these factors and their impact on food prices is crucial for designing effective risk management strategies and policy interventions. By integrating relevant data sources and leveraging ML algorithms, this project seeks to identify key drivers of food price volatility and develop predictive models capable of capturing their nuanced interactions.

Limited Access to Timely and Accurate Price Information: Inadequate availability of timely and accurate price information poses a significant challenge for market participants, particularly smallholder farmers, traders, and consumers, who rely on such information for decision-making. By leveraging ML techniques to analyze historical price data and real-time market signals, this project aims to provide stakeholders with actionable insights and price forecasts, empowering them to make informed choices and navigate market uncertainties more effectively.

## 1.3 Aim and Objectives

The project aims to develop a robust

The specific objectives of this work are summarized as:

## 1.4 Methodology

In addressing the challenge of food price forecasting and prediction using Machine Learning (ML), it is essential to adopt a comprehensive methodology that encompasses data collection, preprocessing, model selection, training, evaluation, and deployment. This section outlines the methods, models, and evaluation metrics that can be utilized in this project.

### 1.4.1 Overview of Methods

1. Data Collection: The first step involves gathering relevant Historical Price Data from various sources, and collecting historical prices of key food commodities from market reports, government databases, and online sources.
2. Data Preprocessing: Preprocessing ensures that the data is clean, relevant, and formatted correctly for ML models. This involves data cleaning (handling missing values, outliers, and inconsistencies in the data), feature engineering (creating new features from raw data to enhance model performance, generating lagged price variables to capture temporal dependencies), normalization and scaling of features to ensure that they contribute equally to the model training process, data splitting (dividing the data into training, validation, and test sets to enable model training and evaluation).
3. Model Selection: Selecting appropriate ML models is crucial for accurate predictions. Several models can be considered such as Linear Regression (A basic model that can be used for initial benchmarking. It assumes a linear relationship between input features and the target variable), Decision Trees (A non-linear model that splits the data into subsets based on feature values, useful for capturing complex patterns), Random Forests (An ensemble method that builds multiple decision trees and averages their predictions to improve accuracy and prevent overfitting), Gradient Boosting Machines (GBM) (An advanced ensemble technique that builds models sequentially to correct the errors of previous models, enhancing predictive performance), Support Vector Machines (SVM) (A model that finds the optimal hyperplane to separate data points, effective for high-dimensional data), Neural Networks (Deep learning models, especially Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, which are particularly effective for time-series forecasting), etc.
4. Model Training and Validation: Training the selected models on the training dataset and tuning hyperparameters using the validation dataset. Techniques like cross-validation can be employed to ensure robust performance.
5. Model Evaluation: Evaluating the performance of the trained models using various metrics to ensure their accuracy and reliability. Key evaluation metrics include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R-squared (R²), and Mean Absolute Percentage Error (MAPE).
6. Model Deployment: Deploying the best-performing model to a production environment where it can make real-time predictions. This involves integrating the model into a software application or web service that can handle incoming data and output predictions, continuous monitoring of the model's performance over time to detect any degradation in accuracy and retraining the model with new data as needed, developing a user-friendly interface for stakeholders to interact with the model, visualize predictions, and make informed decisions.

By employing these methods, models, and evaluation metrics, this project aims to develop robust and accurate food price forecasting tools. These tools will enable better decision-making, enhance market stability, and contribute to improved food security in Nigeria.

## 1.5 Significance of the Study

This project covers discussions and the implementation of machine learning techniques in predicting Nigerian food prices. The project holds the potential to bring about transformative changes and address critical challenges in Nigeria's agricultural sector. Some of the key significance of the project include:

Enhancing Food Security: Accurate prediction of food prices enables stakeholders to anticipate market dynamics and plan production, distribution, and procurement strategies accordingly. By providing timely insights into price trends and fluctuations, the project empowers policymakers and food security agencies to implement targeted interventions, mitigate supply chain disruptions, and ensure the availability and affordability of essential food commodities for all Nigerians.

Improving Market Efficiency: Predictive models developed through the project facilitate better market planning, resource allocation, and risk management practices, thereby enhancing the efficiency and resilience of agricultural markets in Nigeria. By reducing information asymmetry and uncertainty, the project contributes to fairer pricing mechanisms, transparent transactions, and smoother market operations, benefiting farmers, traders, and consumers alike.

Empowering Stakeholders: The project equips stakeholders with valuable tools and insights to make informed decisions, mitigate risks, and seize opportunities in the agricultural market. Farmers can leverage price forecasts to optimize crop selection, planting schedules, and marketing strategies, improving their profitability and livelihoods. Traders and retailers can better manage inventory, pricing, and procurement decisions, enhancing their competitiveness and market position. Consumers can plan their food budgets more effectively, particularly in times of price volatility, ensuring access to nutritious and affordable food options.

Informing Policy Formulation: The project's findings and recommendations provide valuable inputs for evidence-based policy formulation and strategic planning in the agricultural sector. Policymakers can utilize price prediction models to design targeted interventions, subsidy programs, and market regulations aimed at stabilizing food prices, promoting market integration, and addressing regional disparities. Moreover, insights from the project contribute to broader policy discussions on trade, investment, and agricultural development, fostering a conducive environment for sustainable growth and poverty reduction.

Promoting Economic Stability: Food price stability is critical for macroeconomic stability and social cohesion in Nigeria. Fluctuations in food prices can have cascading effects on inflation, household incomes, and overall economic performance. By helping to mitigate price volatility and market uncertainties, the project contributes to economic stability, reduces inflationary pressures, and enhances social welfare, thereby fostering a conducive environment for inclusive growth and development.

Fostering Technological Innovation: The project fosters innovation and technological advancement in the agricultural sector by leveraging cutting-edge machine learning techniques and data analytics. By demonstrating the potential of ML-based solutions for addressing real-world challenges, the project encourages further research, investment, and adoption of digital technologies in agriculture, paving the way for a more resilient, productive, and sustainable food system in Nigeria.

By harnessing the power of data-driven insights and predictive analytics, the project contributes to building a more resilient, inclusive, and prosperous agricultural economy, ultimately benefiting millions of Nigerians and advancing the nation's development agenda.

## 1.6 Definition of Terms

1. Machine Learning (ML): A branch of artificial intelligence that involves the development of algorithms and statistical models that enable computers to learn from and make predictions or decisions based on data.
2. Food Security: The state in which all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life.
3. Food Price Volatility: The degree of variation in food prices over time, often influenced by factors such as supply and demand, weather conditions, economic policies, and market speculation.
4. Predictive Model: A statistical or computational model used to forecast future data points by analyzing patterns in historical and current data.
5. Time Series Forecasting: A method of predicting future values based on previously observed values, commonly used in the context of time-dependent data.
6. Linear Regression: A basic predictive model that assumes a linear relationship between input features and the target variable.
7. Decision Trees: A non-linear model that splits data into subsets based on feature values to make predictions, capturing complex patterns in the data.
8. Random Forests: An ensemble learning method that builds multiple decision trees and averages their predictions to improve accuracy and prevent overfitting.
9. Gradient Boosting Machines (GBM): An advanced ensemble technique that builds models sequentially to correct the errors of previous models, enhancing predictive performance.
10. Support Vector Machines (SVM): A model that finds the optimal hyperplane to separate data points, effective for high-dimensional data.
11. Neural Networks: Deep learning models that simulate the workings of the human brain, particularly effective for complex pattern recognition and time-series forecasting.
12. Recurrent Neural Networks (RNN): A type of neural network designed for sequential data, where connections between nodes form a directed graph along a temporal sequence.
13. Long Short-Term Memory (LSTM): A type of RNN capable of learning long-term dependencies, particularly useful for time-series forecasting.
14. Mean Absolute Error (MAE): An evaluation metric that measures the average magnitude of the errors in a set of predictions, without considering their direction.
15. Root Mean Squared Error (RMSE): An evaluation metric that measures the square root of the average of the squared differences between predicted and actual values.
16. R-squared (R²): A statistical measure that represents the proportion of the variance for the target variable that is explained by the input features in the model.
17. Mean Absolute Percentage Error (MAPE): An evaluation metric that measures the average percentage error between predicted and actual values, providing a percentage-based assessment of prediction accuracy.
18. Feature Engineering: The process of creating new input features from raw data to improve the performance of machine learning models.
19. Normalization and Scaling: Techniques used to adjust the range of input features so that they contribute equally to the model training process.
20. Cross-Validation: A technique used to evaluate the performance of a model by dividing the data into multiple subsets, training the model on some subsets while validating it on others.
21. Hyperparameter Tuning: The process of adjusting the parameters of a machine learning model to optimize its performance.
22. Data Preprocessing: The steps taken to clean and prepare raw data for analysis and model training, including handling missing values, outliers, and inconsistencies.
23. Post-Harvest Losses: The losses that occur in the supply chain from the time of harvest until the food reaches the consumer, including losses during storage, transportation, and processing.
24. Supply Chain: The entire network of entities involved in producing, handling, and distributing a specific product, from raw material suppliers to final consumers.
25. Socioeconomic Indicators: Quantitative measures that describe the economic and social conditions of a population, often used to understand the broader context affecting food prices.

# 

# LITERATURE REVIEW

## 2.1 Food and Food Prices

Food is a fundamental necessity for human survival and well-being. It provides the essential nutrients required for the body's growth, repair, and maintenance. Beyond its physiological importance, food also plays a critical role in social and cultural contexts, symbolizing tradition, identity, and community. The availability, quality, and variety of food have significant implications for public health, economic stability, and overall quality of life. A well-nourished population is more productive, healthier, and more capable of contributing to societal advancement.

The importance of food cannot be overstated, as it directly affects both physical and mental health. Good nutrition is linked to improved cognitive function, enhanced mood, and better resistance to illness. Conversely, malnutrition and food insecurity can lead to a range of health problems, including stunted growth in children, weakened immune systems, and increased susceptibility to chronic diseases. Therefore, ensuring access to sufficient, safe, and nutritious food is a primary goal for governments and organizations worldwide (S. Hendriks et al, 2021).

Food prices are a critical factor in determining access to adequate nutrition. They are influenced by a myriad of factors, including production costs, supply chain logistics, market demand, and external conditions such as weather patterns and geopolitical events. Food prices affect both consumers and producers, shaping their economic behavior and influencing decisions related to production, consumption, and trade.

From an economic perspective, food prices are subject to the laws of supply and demand. When supply decreases or demand increases, prices typically rise. Conversely, when supply increases or demand decreases, prices tend to fall. However, the food market is complex, and prices are often influenced by more than just supply and demand dynamics. For example, production costs can be affected by the price of inputs such as seeds, fertilizers, and labour. Transportation and storage costs, which are crucial for perishable goods, also play a significant role. Moreover, food prices are often subject to seasonal variations (Food and Agriculture Organization, 2011). Certain crops are only available at specific times of the year, leading to fluctuations in prices based on the harvest cycle. Additionally, global market trends and trade policies can impact domestic food prices. For instance, changes in import tariffs or export restrictions can alter the availability and cost of food products.

The economics of food prices involves understanding the various elements that cause prices to change over time. Key factors include changes in the cost of inputs such as seeds, fertilizers, and fuel directly impact food production costs. An increase in these costs typically leads to higher food prices. Adverse weather conditions, such as droughts, floods, or unseasonable temperatures, can reduce crop yields and disrupt food supply chains, leading to higher prices. Climate change poses a long-term risk by increasing the frequency and severity of such events. Shifts in consumer preferences and population growth can drive changes in demand for specific food items. For example, increasing urbanization and rising incomes may lead to higher demand for processed and imported foods. International trade policies, such as tariffs and trade agreements, can influence domestic food prices. Global market conditions, including commodity prices and currency exchange rates, also play a role. Inefficiencies in transportation, storage, and distribution can lead to significant post-harvest losses and increased costs, which are often passed on to consumers.

Understanding these factors is crucial for developing strategies to manage food price volatility and ensure food security. Predicting and mitigating the impact of these variables can help stabilize food markets and protect vulnerable populations from price shocks.

Nigeria, with its large and growing population, faces unique challenges in managing food prices. The country is characterized by a diverse agricultural sector that produces a wide range of crops and livestock. However, despite its potential, Nigeria's food system is often hampered by various structural issues that contribute to price instability.

One significant factor affecting food prices in Nigeria is the high level of dependency on smallholder farmers, who often lack access to modern farming technologies and financial resources. This limitation results in lower productivity and higher vulnerability to environmental shocks. Additionally, Nigeria's agricultural sector is highly susceptible to climate change, with unpredictable weather patterns adversely affecting crop yields.

Inflation and economic instability also play a role in food price dynamics. High inflation rates can erode purchasing power, making it more difficult for consumers to afford basic food items. Moreover, fluctuations in the exchange rate can impact the cost of imported food products, further contributing to price volatility.

Another critical issue is the inefficiency of the food supply chain. Poor infrastructure, inadequate storage facilities, and transportation challenges lead to significant post-harvest losses. It is estimated that Nigeria loses a substantial portion of its agricultural produce before it reaches the market. These losses not only reduce the overall supply of food but also drive up prices due to increased scarcity.

Furthermore, socio-political factors, such as conflicts and instability in certain regions, can disrupt agricultural activities and food distribution networks. These disruptions often lead to localized food shortages and price spikes, exacerbating food insecurity.

Given these complexities, there is a clear need for robust methods to predict and manage food prices in Nigeria. Accurate forecasting can help stakeholders, including policymakers, farmers, and consumers, make informed decisions to mitigate the adverse effects of price volatility. This brings us to the importance of time series forecasting in the context of food prices.

## 2.2 Time Series Trends, Analysis, and Forecasting

A time series is a sequence of data points recorded at successive points in time, often at regular intervals such as daily, monthly, or annually. These data points reflect the changes in a variable over time, allowing for the analysis of patterns and the prediction of future values. Time series data are commonly used in various fields, including economics, finance, environmental studies, and social sciences, to study trends, seasonal variations, and other temporal patterns.

### 2.2.1 Time Series Trends

A trend in a time series represents the long-term movement or direction in the data over an extended period. It indicates a persistent increase or decrease in the variable being measured, ignoring short-term fluctuations. Trends can be linear or nonlinear, and identifying them is crucial for understanding the underlying behaviour of the time series and making accurate forecasts. Types of Trends include

Linear Trends: Represented by a straight line, linear trends show a consistent upward or downward movement in the data. For example, a consistent rise in a company's sales over several years would indicate a linear upward trend.

Nonlinear Trends: These trends do not follow a straight line and can take various forms, such as exponential or logarithmic growth. Nonlinear trends are often observed in biological populations, technological advancements, and economic growth patterns.

Seasonal Trends: These are patterns that repeat at regular intervals, such as monthly or quarterly. Seasonal trends are common in retail sales, agricultural production, and energy consumption.

Cyclical Trends: Unlike seasonal trends, cyclical trends do not follow a fixed calendar pattern but rather reflect long-term economic cycles, such as business cycles. These trends can last for several years and are influenced by broader economic factors.

### 2.2.2 Time Series Analysis

Time series analysis involves the examination of time-ordered data to identify patterns, trends, and other meaningful characteristics. The goal is to understand the underlying structure and dynamics of the series to make informed predictions and decisions. Steps in Time Series Analysis include;

a. Data Collection: Gathering the relevant time series data. This may involve collecting historical data on the variable of interest from various sources.

b. Data Cleaning: Preparing the data for analysis by handling missing values, outliers, and other inconsistencies. This step ensures the data is accurate and reliable.

c. Exploratory Data Analysis (EDA): Visualizing the data using plots and charts to identify patterns, trends, and anomalies. EDA helps in understanding the basic structure of the time series.

d. Decomposition: Separating the time series into its constituent components: trend, seasonal, and residual (noise) components. This step helps in isolating and analyzing each aspect of the series.

e. Stationarity Testing: Checking if the time series is stationary, meaning its statistical properties, such as mean and variance, remain constant over time. Non-stationary series may require differencing or transformation to achieve stationarity.

f. Model Selection: Choosing the appropriate models for the time series analysis based on the identified patterns and characteristics.

#### 2.2.2.1 Types of Time Series Patterns

Time series data analysis involves identifying various patterns that provide insights into the underlying dynamics of the data over time. These patterns shed light on the trends, fluctuations, and noise present in the dataset, enabling you to make informed decisions and predictions. Let's explore some of the prominent time series patterns that help us decipher the intricate relationships within the data and leverage them for predictive analytics.

From discerning trends and seasonality to identifying cyclic patterns and understanding the impact of noise, each pattern contributes to our understanding of the data's behavior over time. Additionally, time series regression introduces a predictive dimension, allowing you to forecast numerical values based on historical data and the influence of other variables.

Delving into the below patterns not only offers a world of insights within time-dependent data but also unearths distinct components that shape its narrative:

Trends: Trends represent long-term changes or movements in the data over time. These can be upward (increasing trend) or downward (decreasing trend), indicating the overall direction in which the data is moving.

Seasonality: Seasonality refers to repeating patterns or fluctuations that occur at regular intervals. These patterns might be daily, weekly, monthly, or yearly, depending on the nature of the data.

Cyclic Patterns: Unlike seasonality, cyclic patterns are not fixed to specific intervals and may not repeat at regular frequencies. They represent oscillations that are not tied to a particular season.

Noise: Noise is the random variation present in the data which does not follow any specific pattern. It introduces randomness and uncertainty to the time series.

Regression: Time series regression involves building a predictive model to forecast a continuous numerical value (the dependent variable) based on historical time series data of one or more predictors (independent variables).

### 2.2.3 Preprocessing Techniques for Time Series Data

Before applying any prediction model, proper preprocessing is essential for time series data. Some common preprocessing techniques include:

Handling Missing Values: Addressing missing values is crucial as gaps in the data can affect the model's performance. You can use techniques like interpolation or forward/backward filling.

Data Normalization: Normalizing the data ensures that all features are on the same scale, preventing any single feature from dominating the model's learning process.

Detrending: Removing the trend component from the data can help in better understanding the underlying patterns and making accurate predictions.

Seasonal Adjustment: For data with seasonality, seasonal adjustment methods like seasonal differencing or seasonal decomposition can be applied.

Smoothing: Smoothing techniques like moving averages can be used to reduce noise and highlight underlying patterns.

Train-test Split: It is crucial to split the data into training and test sets while ensuring that the temporal order is maintained. This allows the model to learn from past input data of the training set and evaluate its performance on unseen future data.

### 2.2.4 Time Series Forecasting

Time series forecasting involves predicting the future values of a variable based on its historical data. Accurate forecasting is essential for decision-making in various fields, such as finance, economics, and supply chain management. Helps in planning and allocating resources efficiently, such as budgeting and staffing in businesses. Assists in maintaining optimal inventory levels by predicting future demand for products. Aids in identifying potential risks and preparing mitigation strategies in advance. Informs government policies and strategies based on anticipated trends in economic indicators, population growth, and other variables.

Various models are used for time series forecasting, each with its strengths and limitations. The choice of model depends on the nature of the data and the forecasting objectives.

a. Naive Methods:

Naive Forecasting: Assumes that the future value is equal to the most recent observed value. It is simple but often serves as a benchmark.

Seasonal Naive Forecasting: Assumes that the future value is equal to the value from the same season in the previous period.

b. Moving Averages:

Simple Moving Average (SMA): Averages a fixed number of past observations to smooth out short-term fluctuations and highlight longer-term trends.

Exponential Moving Average (EMA): Applies more weight to recent observations, making it more responsive to recent changes.

Autoregressive Integrated Moving Average (ARIMA) Models: Combine autoregressive (AR) and moving average (MA) components with differencing to achieve stationarity. ARIMA is powerful for capturing different types of time series patterns.

Seasonal ARIMA (SARIMA) Models: Extend ARIMA to handle seasonal patterns by incorporating seasonal differencing and seasonal autoregressive and moving average components.

c. Exponential Smoothing:

Simple Exponential Smoothing (SES): Assigns exponentially decreasing weights to past observations, suitable for data with no trend or seasonality.

Holt’s Linear Trend Model: Extends SES by adding a trend component, useful for data with a linear trend.

Holt-Winters Seasonal Model: Further extends Holt’s model by adding a seasonal component, ideal for data with both trend and seasonality.

d. Machine Learning Models:

Random Forest: An ensemble learning method that builds multiple decision trees and aggregates their predictions, effective for capturing complex patterns.

Support Vector Machines (SVM): Finds the optimal hyperplane that maximizes the margin between different classes, useful for high-dimensional data.

Neural Networks: Deep learning models, such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, are particularly effective for capturing intricate temporal dependencies.

Time Series Price Forecasting

Time series price forecasting specifically focuses on predicting future prices of commodities, financial assets, or other goods and services. This type of forecasting is crucial in various sectors, including agriculture, finance, and retail, where price fluctuations significantly impact decision-making and strategic planning.

Challenges in time series price forecasting include volatility, where prices can be highly erratic due to various factors such as market demand, geopolitical events, and economic policies. Additionally, data quality poses a significant challenge, as accurate forecasting necessitates high-quality, reliable data, which can be difficult to obtain. The complexity of capturing the interplay of multiple factors influencing prices further complicates forecasting efforts, requiring sophisticated models and techniques. To improve forecast accuracy, integrating multiple data sources, such as historical prices, weather patterns, and economic indicators, can enhance model precision. Employing advanced machine learning models capable of capturing complex patterns and relationships in the data is crucial. Furthermore, continuously updating models with new data ensures their predictive performance improves over time, addressing the dynamic nature of price fluctuations.

In conclusion, time series analysis, trends, and forecasting play a crucial role in understanding and predicting temporal patterns in various domains. By leveraging appropriate models and techniques, stakeholders can make informed decisions, optimize resource allocation, and mitigate risks effectively.

## 2.3 Artificial Intelligence

Artificial intelligence (AI) is a field in computer science that aims to create machines capable of intelligent behaviour. It encompasses various techniques and methodologies that enable computers to perform tasks that typically require human intelligence, such as learning from data, reasoning, problem-solving, perception, natural language understanding, and decision-making.

One comprehensive definition of artificial intelligence is provided by Stuart and Peter (2021) in the 4th edition of  their widely used textbook "Artificial Intelligence: A Modern Approach, Global Edition." They define artificial intelligence as:

"The study of agents that receive percepts from the environment and perform actions."

This definition highlights the key aspects of AI, including the perception of the environment, decision-making, and the pursuit of goals. It emphasizes the notion of intelligent agents that can interact with their environment to achieve desired outcomes.

In the context of this project, AI encompasses the development and application of intelligent algorithms that can learn from data to make predictions about future food prices. AI enables the automation of data analysis and prediction, making it possible to handle large datasets efficiently and derive meaningful insights.

### 2.3.1 Application of Artificial Intelligence

AI has a diverse range of applications across various domains. AI is revolutionizing various sectors, transforming tasks, decision-making, and problem-solving processes. In agriculture, AI is used for crop yield prediction, price forecasts, intelligent spraying, predictive insights, agricultural robots, disease diagnosis, and crop and soil monitoring.

A blue circle with text

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Figure 2.1  Applications of Artificial Intelligence in Agriculture (Javatpoint 2021)

The finance sector leverages AI for algorithmic trading, fraud detection, risk assessment, and customer service. Healthcare benefits from AI through medical image analysis, drug discovery, personalized medicine, and patient management systems. In transportation, AI is applied to autonomous vehicles, traffic management systems, predictive maintenance for infrastructure, and route optimization. Education utilizes AI for adaptive learning platforms, intelligent tutoring systems, and educational content creation. Manufacturing sees AI-enabled robotics, predictive maintenance, quality control, and supply chain optimization enhancing processes. Entertainment employs AI in content recommendation systems, gaming AI, virtual reality, and augmented reality applications. These examples highlight AI's broad impact across industries, with its applications expected to expand further, shaping the future of technology and society

## .

A group of people working on a robot

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Figure 2.2  Applications of Artificial Intelligence (Techvidvan 2024)

## 2.3.2 Branches of Artificial Intelligence

1. Machine Learning (ML):

Machine learning focuses on developing algorithms and statistical models that enable computers to learn from and make predictions or decisions based on data. It encompasses supervised learning, unsupervised learning, and reinforcement learning techniques. ML algorithms are used in various applications such as image recognition, speech recognition, natural language processing, and recommendation systems. (Goodfellow *et al.*, 2016).

1. Natural Language Processing (NLP):

Natural Language Processing deals with the interaction between computers and humans through natural language. It involves tasks such as language understanding, language generation, and language translation. NLP techniques are used in applications like chatbots, sentiment analysis, machine translation, and speech recognition. (Jurafsky *et al.*, 2019)

1. Computer Vision (CV):

Computer vision aims to enable computers to interpret and understand the visual world. It involves tasks such as image recognition, object detection, image segmentation, and scene understanding. CV techniques find applications in autonomous vehicles, medical image analysis, surveillance systems, and augmented reality. (Szeliski *et al.*, 2010).

1. Robotics:

Robotics is an interdisciplinary branch of AI focused on the design, construction, operation, and use of robots. It integrates aspects of mechanical engineering, electrical engineering, and computer science. Robotics encompasses areas such as robot perception, motion planning, manipulation, and human-robot interaction. (Siciliano *et.al.,* 2016).

1. Expert Systems:

Expert systems emulate the decision-making ability of a human expert in a specific domain. These systems use knowledge representation, inference mechanisms, and expert knowledge to provide solutions to complex problems. Expert systems find applications in fields such as medicine, finance, engineering, and troubleshooting. (Buch *et al.*, 2021).

1. Reinforcement Learning:

Reinforcement learning is a branch of machine learning concerned with how software agents ought to take actions in an environment to maximize some notion of cumulative reward. It involves learning through trial and error, where agents learn optimal behaviour by interacting with the environment. Reinforcement learning is used in applications such as game playing, robotics, autonomous vehicle control, and recommendation systems. (Sutton *et al.*, 2018).

These branches of Artificial Intelligence represent key areas of research and application, each with its own set of techniques, methodologies, and challenges. These branches of Artificial Intelligence consist of algorithms which seek to create expert systems which make predictions or classifications based on input data. The applications of this technology are growing daily, and researchers are just starting to explore the possibilities.

## 2.4 Machine Learning (ML)

Machine learning is a subfield of artificial intelligence (AI) that focuses on developing algorithms and models that enable computers to learn from data and make predictions or decisions without explicit programming. In traditional programming, humans provide explicit instructions for a computer to perform a task. In contrast, machine learning algorithms use patterns and insights derived from data to improve their performance over time The concept of machine learning has evolved over several decades, with its roots tracing back to the mid-20th century. In 1959, Arthur Samuel, a pioneer in the field, defined machine learning as the ability to learn without being explicitly programmed. Early developments focused on symbolic methods and knowledge-based approaches. The introduction of statistical methods in the 1980s and 1990s marked a significant shift, enabling the development of algorithms that could learn from large datasets.

The advent of big data and the increase in computational power in the 2000s accelerated the progress of ML, leading to the development of more sophisticated algorithms and models. Today, ML is a crucial component of AI, driving advancements in various industries, from healthcare and finance to agriculture and entertainment. The goal is to enable computers to generalize from past experiences and adapt to new situations without being programmed for each scenario. For example, the system receives certain data as input, recognizes patterns in the data, and outputs its responses. In this instance, the system learns a great deal over time on its own without the help of humans. It uses an algorithm for statistical learning that learns and gets better independently without human assistance (Neha et al., 2021).

Machine learning is a dynamic and rapidly evolving field that plays a critical role in advancing technology and society. Its ability to learn from data and make accurate predictions makes it an invaluable tool for solving complex problems across diverse sectors. By understanding the fundamental concepts, algorithms, and applications of ML, stakeholders can harness its full potential to drive innovation, efficiency, and positive change.

### 2.4.1 Classifications of Machine Learning:

Machine Learning can be broadly classified into four categories: Supervised learning, Semi-supervised learning, unsupervised learning, and Reinforcement Learning.

a. Supervised learning: Supervised learning involves training a model on a labeled dataset, where the input features and the corresponding output labels are known. The model learns to map inputs to outputs based on the training data, enabling it to make predictions on new, unseen data. (Goodfellow *et al.*, 2016). Common supervised learning algorithms include Linear Regression, Logistic Regression, Decision Trees, Support Vector Machines (SVM), and Neural Networks.

b. Semi-supervised learning: Semi-supervised learning is a type of machine learning that falls in between supervised and unsupervised learning. It is a method that uses a small amount of labelled data and a large amount of unlabeled data to train a model. Semi-supervised learning is particularly useful when there is a large amount of unlabeled data available, but it’s too expensive or difficult to label all of it. Semi-supervised learning aims to learn a function that can accurately predict the output variable based on the input variables, similar to supervised learning. However, most semi-supervised methods perform poorly when there are many noises and redundant information in the original data.(Jiaqi *et al.,* 2024). Examples of Semi-Supervised Learning include Text classification, Image classification, and Anomaly detection.

c. Unsupervised learning: this is a type of machine learning where algorithms are trained on input data without explicit supervision or labelled responses. Instead of being given labelled examples, the algorithm learns to identify patterns or structures in the input data on its own. Common tasks in unsupervised learning include clustering, dimensionality reduction, and density estimation. Unsupervised learning is particularly useful when labelled data is scarce or expensive to obtain. (Bengio *et al.*, 2017). Common unsupervised learning techniques include clustering algorithms like K-means, Hierarchical clustering and Dimensionality Reduction Methods like PCA and t-SNE.

d. Reinforcement learning is a type of machine learning where an agent learns to make decisions by interacting with an environment. The agent learns through trial and error, receiving feedback in the form of rewards or penalties based on its actions. The objective of reinforcement learning is to learn a policy that maximizes the cumulative reward over time. It is often used in sequential decision-making tasks, such as game-playing, robotics, and autonomous vehicle control (Sutton *et al.*, 2018). Key concepts in reinforcement learning include Markov Decision Processes (MDPs), Q-Learning, and Policy Gradients.

## 2.5 Machine Learning Algorithms and Techniques

a. Linear and Logistic Regression

Linear regression models the relationship between input features and a continuous target variable using a linear equation. It is simple yet effective for many applications. Logistic regression, on the other hand, is used for binary classification, predicting the probability of an outcome based on input features.

b. Decision Trees and Ensemble Methods

Decision trees split the data into subsets based on feature values, creating a tree-like model of decisions. Ensemble methods like Random Forests and Gradient Boosting Machines (GBM) combine multiple decision trees to improve accuracy and reduce overfitting. Random Forests aggregate the predictions of multiple trees, while GBMs build trees sequentially to correct the errors of previous models.

c. Support Vector Machines (SVM)

Support Vector Machines find the optimal hyperplane that separates data points into different classes. They are particularly effective in high-dimensional spaces and for complex classification tasks.

d. Naive Bayes Algorithm

A Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature. Even if these features are related to each other, a Naive Bayes classifier would consider all of these properties independently when calculating the probability of a particular outcome. A Naive Bayesian model is easy to build and useful for massive datasets. It's simple and is known to outperform even highly sophisticated classification methods.

e. KNN (K- Nearest Neighbors) Algorithm

This algorithm can be applied to both classification and regression problems. It’s a simple algorithm that stores all available cases and classifies any new cases by taking a majority vote of its k neighbors. The case is then assigned to the class with which it has the most in common. A distance function performs this measurement. KNN is computationally expensive as data still needs to be pre-processed ensuring variables are normalized, or else higher range variables can bias the algorithm.

f. K-Means

It is an unsupervised learning algorithm that solves clustering problems. Data sets are classified into a particular number of clusters in such a way that all the data points within a cluster are homogenous and heterogeneous from the data in other clusters. The K-means algorithm picks k number of points, called centroids, for each cluster. Each data point forms a cluster with the closest centroids, i.e., K clusters. It now creates new centroids based on the existing cluster members. With these new centroids, the closest distance for each data point is determined. This process is repeated until the centroids do not change.

g.  Neural Networks and Deep Learning

Neural networks consist of interconnected layers of nodes, or neurons, that process data and learn patterns. Deep learning, a subset of neural networks, involves multiple hidden layers that enable the model to capture complex patterns and representations in data. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are popular architectures used in image and speech recognition, respectively.

## 2.4 Neural Networks

Neural Networks are a class of machine learning algorithms inspired by the structure and function of the human brain. They consist of interconnected layers of nodes or neurons, which process input data to extract patterns and features. Each neuron performs a weighted sum of its inputs, passes the result through an activation function, and then transmits the output to the next layer of neurons. This process continues until the final layer produces the network's prediction or classification. Neural networks are particularly effective at handling complex, non-linear relationships in data, making them well-suited for tasks such as image and speech recognition, natural language processing, and time-series forecasting.

Neural Networks are a subset of machine learning, which is itself a branch of artificial intelligence (AI). Machine learning involves developing algorithms that can learn from and make predictions or decisions based on data. Neural networks take this concept further by using a layered approach to simulate the way the human brain processes information. While traditional machine learning algorithms may require extensive feature engineering and often struggle with high-dimensional data, neural networks can automatically discover representations and patterns in raw data through a process known as feature learning. The main advantage of using a neural network over traditional machine learning algorithms is its ability to learn a complex mapping from the input space onto the output. It is for this reason neural networks are called universal function approximators. The various parameters of the network (weights) enable the neurons in the different layers to learn other aspects of this mapping.

Neural networks can be classified under deep learning when they consist of many layers (hence "deep" networks), enabling the modeling of complex functions and abstractions in large datasets. This deep learning capability allows neural networks to excel in tasks that are challenging for traditional machine learning methods.

**2.4.1 Types of Neural Networks**

Neural networks come in various forms, each designed to handle specific types of tasks and data structures. Here are the primary types:

a. Feedforward Neural Networks (FNN): The simplest type of artificial neural network, where the data moves in one direction from input nodes, through hidden nodes (if any), and finally to the output nodes. There are no cycles or loops in the network. These are often used for basic tasks like image recognition and classification.

b. Convolutional Neural Networks (CNN): Specialized for processing structured grid data such as images. They use convolutional layers that apply filters to the input data, capturing spatial hierarchies and patterns. CNNs are widely used in image and video recognition tasks.

c. Recurrent Neural Networks (RNN): Designed for sequential data, RNNs have connections that form directed cycles. This structure allows them to maintain information in 'memory' over time, making them suitable for tasks like time-series prediction and natural language processing.

d. Long Short-Term Memory Networks (LSTM): A special kind of RNN capable of learning long-term dependencies. They overcome the limitations of basic RNNs in handling long sequences by using memory cells and gates to control the flow of information.

e. Generative Adversarial Networks (GAN): Consists of two neural networks, a generator and a discriminator, that compete against each other. The generator creates fake data, while the discriminator evaluates it against real data. GANs are used in generating realistic images, videos, and other types of data.

f. Autoencoders: Neural networks trained to copy their input to their output through a compressed representation. They are used for tasks such as dimensionality reduction and anomaly detection.

Neural networks, with their various types and architectures, have revolutionized the field of machine learning by enabling the modelling of complex patterns and relationships in data. From feedforward networks to convolutional networks for image processing, and recurrent networks to LSTM networks for sequence modelling, each type offers unique advantages for specific tasks. RNNs and LSTMs, in particular, have proven invaluable in handling sequential data, overcoming the challenges of long-term dependencies, and enabling significant advancements in natural language processing, time-series forecasting, and beyond. As research and development continue, the capabilities and applications of neural networks are expected to expand further, driving innovation and transforming various industries.

### 2.4.2 Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are a class of neural networks designed for processing sequences of data. Unlike feedforward neural networks, RNNs have a feedback loop that allows information to persist, making them ideal for tasks where context and sequence order are important.

RNNs are explicitly designed to handle sequential data, such as time-series data, text, and audio. They maintain a hidden state that captures information about previous inputs in the sequence. The feedback mechanism enables RNNs to 'remember' previous inputs, providing context for current inputs. This makes them suitable for tasks where past information influences the output, such as language modelling or stock price prediction. Training RNNs involves a variant of the backpropagation algorithm called Backpropagation Through Time (BPTT), which accounts for the sequential nature of the data by unrolling the network through time.

A diagram of a network

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Figure 2.3 (BPTT) Backpropagation through time (Encord, 2023)

RNNs are used for language modeling, text generation, machine translation, and sentiment analysis. RNNs can predict future values based on historical data, making them useful for financial forecasting, weather prediction, and demand forecasting. RNNs process sequences of audio signals to recognize spoken words and phrases.

Basic RNNs struggle with retaining information over long sequences, limiting their effectiveness in tasks that require long-term memory. During training, gradients can become very small (vanish) or very large (explode), making it difficult for the network to learn long-range dependencies.

### 2.4.3 Long Short-Term Memory Networks (LSTM)

Long Short-Term Memory (LSTM) networks are a type of RNN designed to address the limitations of basic RNNs in learning long-term dependencies. Introduced by Hochreiter and Schmidhuber in 1997, LSTMs incorporate a more complex architecture that makes use of components such as cell state and gates, allowing them to maintain and regulate memory over extended sequences.

The LSTM's cell state is a horizontal line running through the network, acting as a conveyor belt to transfer information unchanged. It is controlled by gates that add or remove information. LSTMs have three primary gates: the Forget Gate (Decides what information to discard from the cell state), the Input Gate (Determines which new information to add to the cell state), and the Output Gate (Controls the output based on the cell state and the current input). Gates in LSTM are the sigmoid activation functions i.e they output a value between 0 or 1 and in most of the cases it is either 0 or 1. (“0” means the gates are blocking everything and“1” means gates are allowing everything to pass through it.)

A red line on a black background

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Figure 2.4 The sigmoid function is commonly used for gates in neural networks to ensure the output is always positive and to provide a clear binary decision on whether to keep or discard a particular feature. (Divyanshu, 2018)

A screenshot of a computer

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Figure 2.5 The LSTM Memory Cell (Divyanshu, 2018)

LSTMs work using these components such that at each time step, the LSTM decides how much of the previous cell state to carry forward, how much new information to add, and what the output should be. This gated mechanism allows LSTMs to maintain relevant information over long sequences.

Like RNNs, LSTMs are trained using BPTT, but their architecture helps mitigate the vanishing and exploding gradient problems, enabling them to learn long-term dependencies more effectively.

Applications of LSTMs include Language Modeling and Text Generation, Time-Series Prediction, Speech and Video Processing, etc.

LSTMs can maintain information over long sequences, addressing a significant limitation of basic RNNs. The gated architecture ensures that gradients flow effectively during training, preventing issues related to vanishing and exploding gradients.

LSTMs are computationally intensive due to their complex architecture, making them slower to train compared to simpler neural networks. LSTMs require careful tuning of hyperparameters, such as the number of units in each layer and the learning rate, to achieve optimal performance.

## 2.5 Statistical Models for Time Series Forecasting

Statistical models are mathematical representations that describe the underlying structure of data by capturing relationships between variables. These models rely on statistical theories and methods to estimate, infer, and predict data behaviours. They can be broadly classified into descriptive models, which summarize data features; inferential models, which draw conclusions about populations from sample data; and predictive models, which forecast future data points based on historical data.

The relationship between statistical models and machine learning (ML) is synergistic. Both fields aim to extract insights from data, but they differ in approach and application. Statistical models emphasize understanding the data's underlying distribution and drawing inferences based on established statistical principles. In contrast, ML focuses on building algorithms that learn patterns from data and make predictions with minimal human intervention. Despite these differences, statistical models are integral to ML. Many ML algorithms incorporate statistical concepts, and hybrid approaches often combine the strengths of both fields. For instance, linear regression, a foundational statistical model, serves as a basis for more complex ML algorithms. In the context of time series forecasting, statistical models analyze sequential data points collected over time. They aim to identify patterns, trends, and seasonal variations to predict future values. Time series models must account for temporal dependencies and autocorrelation within the data. Statistical models like ARIMA are often used alongside ML models to enhance predictive accuracy and interpretability.

### 2.5.1 Types of Statistical Models for Time Series Forecasting

This section discusses various models, highlighting those that are appropriate for time series analysis.

a. Autoregressive Integrated Moving Average (ARIMA): is a statistical analysis model that uses time series data to either better understand the data set or to predict future trends. ARIMA models predict future values based on past values, make use of lagged moving averages to smooth time series data and are widely used in technical analysis to forecast future security prices.

b. Exponential Smoothing State Space Model (ETS): The ETS model is another powerful tool for time series forecasting, particularly suitable for data with clear trends and seasonal components. It uses weighted averages of past observations, where the weights decrease exponentially over time.

c. Seasonal Decomposition of Time Series (STL): STL is a method for decomposing time series data into seasonal, trend, and residual components. It is highly effective for visualizing and understanding the structure of the data but is more of a preprocessing step than a standalone forecasting method.

d. Prophet: Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend and typically handles outliers well. Prophet is open-source software released by Facebook's Core Data Science team. (Thomas Chia, 2023)

However, not all statistical models are suitable for time series forecasting, such as Ordinary Least Squares (OLS) Regression, Logistic Regression, ANOVA (Analysis of Variance), and Chi-Square Tests. While OLS regression and logistic regression are powerful statistical tools, they are not designed to handle the temporal dependencies and autocorrelations inherent in time series data. Similarly, ANOVA and Chi-Square Tests are more suited for hypothesis testing and categorical data analysis, respectively, rather than for forecasting.

### 2.5.2 ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model is a popular statistical approach for time series forecasting. It combines three components: autoregression (AR), differencing (I), and moving average (MA).

* Autoregression (AR): This component uses the dependency between an observation and a number of lagged observations.
* Integrated (I): This part involves differencing the data to achieve stationarity, which is essential for reliable forecasting.
* Moving Average (MA): This component uses dependency between an observation and a residual error from a moving average model applied to lagged observations.

ARIMA models are particularly suitable for short-term forecasting when the time series data is stationary or can be made stationary through differencing. They are robust for capturing linear relationships and are effective in handling univariate time series data. However, ARIMA may struggle with non-linear patterns and multivariate datasets.

### 2**.5.3 Prophet Model**

Prophet is an open-source time series forecasting tool developed by Facebook. It is designed to handle data with strong seasonal effects and missing values, making it highly adaptable and user-friendly. Prophet is particularly effective for business forecasting applications where the data exhibits daily, weekly, or yearly seasonality.

Prophet excels in scenarios with missing data and when the data has multiple seasonality components. It allows users to specify custom seasonalities and holiday effects, providing a high degree of flexibility. This makes Prophet suitable for business, finance, and other applications where data seasonality and external events play significant roles. Its ease of use and ability to provide interpretable results make it a powerful tool for both novice and experienced forecasters.

Statistical models play a crucial role in time series forecasting, offering robust frameworks for predicting future data points based on historical patterns. ARIMA and Prophet stand out as highly effective models for their respective strengths in handling linear dependencies and accommodating complex seasonalities and missing data. By understanding the capabilities and limitations of these models, stakeholders can make informed decisions to enhance predictive accuracy and improve planning and resource allocation in various applications, including food price forecasting in Nigeria. As statistical methods continue to evolve and integrate with advanced machine learning techniques, their role in forecasting and decision-making will only grow more significant.

## 2.6 Review of Related Works

Accurately forecasting food prices in Nigeria is vital for ensuring food security, aiding farmers in making informed decisions, and stabilizing the market. Recent advances in machine learning (ML) and artificial intelligence (AI) have shown significant promise in enhancing the precision of such predictions. This essay reviews several studies that employ various ML techniques to forecast agricultural prices, providing insights into their methodologies, results, and potential applications in Nigeria.

Zhang and Tang (2024) tackled the challenge of forecasting agricultural commodity futures prices by developing a hybrid model combining quadratic decomposition technology with the Long Short-Term Memory (LSTM) model. Their approach significantly improved prediction accuracy over single models like RNN and ANN. The VMD-SGMD-LSTM model, in particular, demonstrated superior performance, showcasing the benefits of hybrid models in handling complex time-series data. This approach's applicability to Nigeria's diverse agricultural commodities could offer more accurate and reliable price forecasts.

Chen et al. (2024) focused on vegetable price prediction using a combination of ARIMA and LSTM models. Their study found that this combination outperformed individual models, highlighting the importance of integrating different ML techniques to capture both short-term and long-term trends. This methodology could be particularly beneficial for Nigeria, where vegetable prices are highly volatile and influenced by multiple factors such as seasonality and market dynamics.

Pawar et al. (2023) utilized supervised learning algorithms, specifically the naïve Bayes Gaussian classifier and boosting algorithms, to predict crop prices. Their high-accuracy results underscore the potential of these models to aid farmers in developing sustainable agricultural practices. Applying these techniques in Nigeria could enhance farmers' decision-making processes, enabling them to better plan crop cultivation and marketing strategies.

Sapakova et al. (2023) employed machine learning techniques, including Decision Trees, Random Forest, and Gradient Boosting, to forecast food prices in Kazakhstan. Their study demonstrated that these models significantly improved forecast accuracy, with Gradient Boosting achieving the highest precision. These findings suggest that similar methodologies could be adapted for Nigeria's market, where accurate food price predictions are crucial for cost reduction and inventory management.

Majhi et al. (2023) applied SARIMA, ETS, and FB Prophet models to forecast food price indexes for cereals, millets, and pulses. Their research provided valuable insights into the effectiveness of time-series forecasting techniques in reducing food wastage and improving supply chain management. For Nigeria, employing these models could enhance the predictability of staple food prices, aiding in better inventory and resource management.

Odion et al. (2023) developed a Random Forest-based online machine learning system to predict market prices for various fresh produce items in Nigeria. This system, accessible through a mobile application, provides real-time market insights to smallholder farmers. The model's ability to discriminate between states and offer precise forecasts for diverse produce highlights its potential to support farmers in making informed decisions and improving business returns.

Murugesan and Radha (2021) introduced a hybrid ensemble model combining ARIMA and Support Vector Regression (SVR) for crop price prediction. This model effectively captured both linear and non-linear aspects of the data, resulting in improved prediction accuracy. Implementing such a model in Nigeria could enhance the forecasting accuracy for various agricultural commodities, supporting better market planning and decision-making.

Wamalwa and Muchemi (2020) developed an ANN model to predict maize prices in Kenya, demonstrating its superior accuracy over baseline linear models. Their methodology, which included optimizing hidden neuron configurations, could be adapted for similar commodities in Nigeria. ANN models' ability to handle complex data and provide precise predictions can be instrumental in formulating agricultural policies and strategies.

Jayapal (2022) employed various statistical and machine learning models to predict food demand, including Multiple Linear Regression, Lasso Regression, and Gradient Boosting Regression. The study's comprehensive approach and evaluation metrics offer a robust framework for assessing model efficiency. Such methodologies could be adapted to forecast food demand in Nigeria, aiding in effective supply chain management and reducing food shortages.

In conclusion, the integration of machine learning and hybrid models holds significant potential for enhancing food price predictions in Nigeria. These methodologies can improve the accuracy and reliability of forecasts, aiding in better agricultural planning, market stability, and food security. Adapting these advanced techniques to the Nigerian context can provide farmers, policymakers, and market stakeholders with valuable insights, ultimately contributing to the nation's agricultural development. Table 2.1 presents a summary of the reviewed related works.

## 2.9 Summary Of Related Works

*Table 1: Summary of Related Works*

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **S/N** | **TITLE** | **AUTHORS**  **(YEAR)** | **PROBLEM ADDRESSED** | **METHOD** | **RESULTS** | **STRENGTHS** | **WEAKNESS** |
| 1. | Hybrid Forecasting Model for Agricultural Commodity Futures Prices Prediction. | Zhang and Tang (2024) | The study addresses the challenge of accurately forecasting agricultural commodity futures prices using existing models, which may have limitations in processing complex time series data. | A hybrid forecasting model that combines quadratic decomposition technology with the Long Short-Term Memory (LSTM) model to enhance prediction accuracy. They compare this model with various single artificial intelligence models and decomposition techniques. | The LSTM model outperforms other single models like RNN and ANN in forecasting the futures price of strong wheat.  The VMD-SGMD-LSTM model shows improved prediction accuracy compared to the LSTM model alone.  Demonstrates the effectiveness of the hybrid model in forecasting agricultural commodity futures prices in different scenarios. | Combines the strengths of LSTM for time-series data processing with quadratic decomposition technology, leading to enhanced prediction accuracy.  Provides a comprehensive analysis of different models, offering insights into improving forecasting performance in agricultural commodity markets. | Focuses on a specific agricultural commodity (strong wheat) and may not generalize to other commodities or markets.  The evaluation of the hybrid model's performance could be further enhanced by considering additional metrics or real-world trading implications. |
| 2. | The Price Prediction of Vegetables by Using Machine Learning. | Qiaochu Chen *et al* (2024) | The study focuses on predicting vegetable prices using machine learning algorithms to facilitate decision-making for producers, operators, consumers, and market supervision departments. | The research analyzes various models for vegetable price prediction, including LSTM for long-term sequence data, ARIMA for short-term predictions, and innovative approaches like Lasso regression for feature compression and BP neural networks for model fitting. | The study found that the combination of ARIMA and LSTM outperformed individual models, with an average prediction error of 11.3%, compared to 15.7% for LSTM and 21.1% for ARIMA. | The research provides insights into the value of using machine learning algorithms for vegetable price prediction, offering a comprehensive analysis of different models and their applications in the field. | ARIMA, may not fit well with non-stationary and nonlinear data, LSTM requires a large amount of data for training. Additionally, Lasso regression is sensitive to sample noise, impacting its performance in practical applications. |
| 3. | Crop Price Estimation Using Machine Learning. | Sudarshan Pawar *et al.* (2023) | Tackling the issue of predicting crop prices to assist farmers in making informed decisions about crop selection and pricing strategies. | Supervised machine learning with naïve Bayes Gaussian classifier and boosting algorithm. | High accuracy in crop price prediction, potential to aid farmers in developing sustainable agricultural practices. | Accurate crop price estimation, and potential extension to provide additional agricultural guidance. | Lack of discussion on real-time data integration and scalability for large datasets. |
| 4. | Machine Learning for Predicting Consumer Food Prices in Kazakhstan. | Sapakova *et al*.(2023) | The study focuses on predicting consumer food prices in Kazakhstan using machine learning techniques to aid in cost reduction, inventory management, and demand forecasting in the retail sector. | The researchers employed machine learning methodologies, specifically Decision Trees, Random Forest, and Gradient Boosting, to analyze a dataset sourced from the World Food Programme's price database. These models were trained and tested to assess their accuracy in forecasting food prices. | The study demonstrated that machine learning significantly improved the accuracy of food price forecasts in Kazakhstan. The Gradient Boosting algorithm yielded the most precise forecasts with an accuracy rate of 99%, while the Random Forest model outperformed others in terms of accuracy for consumer food products. | Utilization of machine learning techniques enhanced the accuracy of food price forecasts.  Compares different machine learning algorithms for predicting food prices, providing insights into their effectiveness.  Contributes to the existing literature by focusing on methodological advancements in predicting food prices. | Limited discussion on the specific features or variables used in the machine learning models.  Lack of detailed comparison with traditional econometric models for predicting food prices.  Did not delve into the interpretability of the machine learning models used for forecasting food prices. |
| 5. | Food price index prediction using time series models: A study of Cereals, Millets and Pulses. | Santosh Kumar Majhi *et al.* (2023) | The study aims to predict food price indexes for cereals, millets and pulses in developing countries to assist in effective inventory management and supply chain planning | The research utilizes SARIMA, ETS, and FB Prophet models to forecast food price indexes based on historical data trends. Each model is applied to the test sample to calculate RMSE and MAE values for evaluation. | The study presents the forecasted price indexes for cereals, millets, and pulses using the developed SARIMA, ETS, and FB Prophet models. Evaluation metrics such as RMSE and MAE are compared to assess the performance of each model. | The research provides insights into the effectiveness of time series forecasting techniques in predicting food price indexes, which can aid in reducing food wastage and improving supply chain management in the food industry. | The study does not provide detailed information on the specific dataset used or the exact values of RMSE and MAE for each model's performance. |
| 6. | Towards Improving Farmers' Livelihood in Nigeria through Food Price Forecasting. | Divinefavour Odion *et al*.(2023) | The study addresses the challenges faced by smallholder farmers in Nigeria, particularly in making informed decisions regarding their produce due to limited data availability and historical records beyond 2017. The lack of market-level data poses a significant challenge to accurate price forecasting. | The study develops an online machine learning system based on the Random Forest model to predict market prices for various fresh produce items in each state of Nigeria up to 8 months into the future. The model is benchmarked against a rolling-average baseline, SARIMA, Catboost, and XGboost algorithms. The system is made accessible through an open-access data science mobile application called Coldtivate, providing real-time market insights to smallholder farmers. | The developed machine learning system accurately predicts market prices for tomato, onion, plantain, Irish potato, and sweet potato in each state of Nigeria. The system is capable of discriminating between the 37 states and provides precise forecasts for a diverse assortment of fresh produce items. | Accurate market price predictions for various fresh produce items.  Development of an online machine learning system accessible through a user-friendly mobile application.  Real-time market insights are provided to smallholder farmers to make informed decisions and improve business returns. | Limited historical data beyond 2017 may impact the effectiveness of the forecasting model.  Lack of market-level data poses challenges for accurate price forecasting. |
| 7. | Application of Machine Learning Algorithms to Forecast Prices of Sardinella brasiliensis (Fish) in a South American Supply Center. | Vinícius França *et al.* (2022) | Forecasting prices of Sardinella brasiliensis (Fish) in a South American supply centre using machine learning algorithms. | Utilized machine learning algorithms (LSTM and Fbprophet) for price forecasting. | The models’ predictions presented accurate predictions for min, mcom and max both when prices for Sardinella brasiliensis (Fish) were high or low. | Integration of machine learning algorithms can enhance the accuracy of price forecasts, enabling better planning and resource allocation. | Limited Discussion on Limitations, especially regarding the dataset used for training and testing the models. |
| 8. | Food Security Analysis and Forecasting: A Machine Learning Case Study in Southern Malawi | Shahrzad Gholami *et al*. (2022) | The study aims to predict food insecurity levels in southern Malawi using machine learning techniques trained on high-frequency household survey data. It addresses the challenge of effectively targeting vulnerable households for assistance in humanitarian programming. | The researchers developed a machine learning workflow (MIRA) based on high-frequency household survey data collected in southern Malawi. They used a variety of predictor features from the surveys to train the model to predict food insecurity levels, focusing on the reduced Coping Strategy Index (rCSI) as a measure of food insecurity. | The machine learning model (MIRA) successfully predicted food insecurity outcomes, identifying key predictors of food insecurity in the region. The study demonstrated the potential of using sophisticated algorithms on high-frequency data to improve food security predictions and provide actionable knowledge for stakeholders and authorities. | Successful application of machine learning techniques to predict food insecurity levels in a data-scarce environment.  Identification of key predictors of food insecurity, providing valuable insights for targeted intervention programs.  Contribution to the growing literature on using new approaches to improve predictions of food security. | Limited discussion on the scalability and generalizability of the machine learning model to other regions or datasets.  Lack of detailed analysis on the potential biases or limitations of using high-frequency household survey data for forecasting food security outcomes. |
| 9. | Predicting Food Demand Using Statistical and Machine Learning Models | Sasikumar Jayapal (2022) | The study aims to predict food demand by utilizing statistical and machine learning models to analyze data on aggregated food orders made online over a week. | The researcher employed a combination of statistical models such as Multiple Linear Regression, Lasso Regression, Ridge Regression, Bayesian Ridge Regression, Decision Tree Regression, Random Forest Regression, Gradient Boosting Regression, XGBoost Regression, LightGBM Regression, and CatBoost Regression. Machine learning evaluation metrics like RMSE, MAE, R^2, and model training time were used to assess model efficiency. | The evaluation results for different machine learning models showed varying performance metrics such as RMSE, MAE, and R^2. For instance, Decision Tree Regression had high accuracy with an R^2 of 0.98, while Lasso Regression had lower performance with an R^2 of 0.27. | The study provides a comprehensive analysis of food demand prediction using a variety of statistical and machine-learning models. The use of different evaluation metrics allows for a thorough comparison of model performance. | The study does not delve into the specific features or variables that significantly influence food demand prediction. Additionally, the research did not but could benefit from discussing the interpretability of the models and potential real-world applications in the food industry. |
| 10. | Machine Learning Techniques for Forecasting Agricultural Prices in Odisha, India. | Ranjit Kumar Paul *et al*.(2022) | The study addresses the challenge of accurately forecasting agricultural prices, specifically focusing on brinjal (eggplant) prices in Odisha, India. The goal is to assist stakeholders in making informed decisions in the agricultural market. | The stochastic model i.e. ARIMA and machine learning algorithms (SVR, RF, GRNN, GBM) to predict the price of brinjal. They collected and analyzed market data from various regions in Odisha to develop their forecasting models. The result of prediction performance was measured by four statistics namely ME, MAE, RMSE and MAPE. | For all the markets, machine learning techniques perform better than that of the usual ARIMA model. Among the four machine learning techniques used, in almost all the markets, GRNN performed better. | Effective utilization of machine learning algorithms for agricultural price forecasting.  In-depth analysis of market data from multiple regions in Odisha.  Promising results in terms of accuracy and predictive capabilities. | Limited discussion on the potential challenges or limitations of the machine learning models.  Lack of detailed comparison with traditional statistical models for price forecasting. |
| 11. | Forecasting Agricultural Commodity Price Using Different Models: A Case Study of Widely Consumed Grains in Nigeria | Olajide I. Sanusi *et al* (2022) | The study aims to highlight specific and accurate methods for forecasting prices of commonly consumed grains in Nigeria from January 2017 to June 2020. | Various forecasting models were employed to predict the prices of white maize, local rice, imported rice, and white beans. These models included  ARIMA, STLM, and ANN models, and the hybrid combination of the three models. | The study found that there is no universally suitable technique for all grains; instead, each grain performs better with a specific model. The forecasting accuracy varied across different grains, emphasizing the importance of selecting appropriate models for each commodity. | The study provides valuable insights into the diverse forecasting approaches required for different agricultural commodities, enhancing the understanding of price dynamics in the Nigerian grain market. | The study's focus on a specific period and region may limit the generalizability of the findings to other contexts or timeframes. |
| 12. | Automated Agriculture Commodity Price Prediction System with Machine Learning Techniques. | Zhiyuan Chen *et al*. (2021) | The research aims to design an automated agriculture commodity price prediction system using machine learning techniques to assist the government and farmers in better agricultural planning. | The study compares five algorithms (ARIMA, SVR, Prophet, XGBoost, LSTM) to determine the most optimal algorithm for accurate price forecasting. Data from FAMA, Malaysia's official government website is used, including both time-series and multivariable datasets. | The system includes a web app with features like sign-up, login, forecast display, commodity information, user profile, and enquiry page. Users can choose the duration of prediction, rescale the graph, and access different models for price forecasting. The system provides a clear visualization of forecast results and separates past prices from forecast results. | Utilizes machine learning techniques for accurate agriculture price forecasting  Provides a user-friendly web interface with various functionalities  Incorporates both time-series and multivariable datasets for analysis. | Limited discussion on the specific performance comparison of the five algorithms  Lack of detailed information on the training and validation processes for the models. |
| 13. | Machine Learning for Price Prediction in Agriculture | Sussy Bayona-Oré *et al*.  (2021) | Predicting prices of agricultural products to assist family farms in decision-making on what to plant for optimal harvest revenue. | Literature review of studies using machine learning models for price prediction in agriculture. | Preference for Neural Network-based algorithms due to their accuracy and precision in price prediction compared to other models. | Provides valuable insights for the research community, farmers, and specialists interested in price prediction for agricultural products. | Lack of specific details on the individual studies reviewed, such as publication years and authors. |
| 14. | Food Demand Prediction Using Nonlinear Autoregressive Exogenous Neural Network. | Sudarshan Pawar *et al.* (2021) | Addressing the challenge of accurately forecasting food demand to support intelligent management systems in the supply chain. | Nonlinear Autoregressive Exogenous Neural Network (NARXNN) hybrid technique. | Effective prediction models for food demand, practical application in intelligent management systems, and support for rational control of food inventory and production. | Novel application of the hybrid technique - Nonlinear Autoregressive Exogenous Neural Network (NARXNN). | Limited discussion on the scalability and generalizability of the model. |
| 15. | Time Series Forecasting of Price of Agricultural Products Using Hybrid Methods | Sourav Kumar Purohit *et al* (2021) | The study focuses on accurately predicting crop prices to assist farmers in optimal selling times and help governments in post-harvest storage and price stabilization throughout the year. | The authors considered statistical methods (ARIMA, ETS), machine learning techniques (MLP, SVM, LSTM), and novel hybrid models to predict the prices of agricultural products such as tomatoes, potatoes, and onions. They introduced innovative hybrid approaches like Additive-ETS-SVM, and Multiplicative-ARIMA-LSTM, among others, and assessed their effectiveness in forecasting the prices of horticultural commodities | Different hybrid methods were found to outperform individual models in predicting crop prices. The Additive-ARIMA-ANN method provided the best forecasts for onion prices, while the Multiplicative-ETS-SVM method excelled in predicting potato prices. The study highlighted the need for diverse methods for different crop price time series data. | Hybrid methods showed improved forecasting accuracy compared to standalone models.  Proposed models tailored to specific crop price time series data.  Comprehensive evaluation of various statistical and machine learning techniques. | No single method provided the best forecasts for all crop prices.  The study focused on specific horticultural commodities and may require adaptation for other agricultural products.  Limited discussion on the interpretability of the hybrid models. |
| 16. | Prediction of Food Production Using Machine Learning Algorithms of Multilayer Perceptron and ANFIS | Saeed Nosratabadi et al. (2021) | The study aims to enhance the accuracy of food production prediction to support food security management, particularly in regions facing challenges like water scarcity and poor water management. e.g Iran | The research employs Adaptive Network-Based Fuzzy Inference System (ANFIS) and Multilayer Perceptron (MLP) models to predict livestock and agricultural production quantities based on time-series data. | The models were trained on 70% of the data and tested on the remaining 30%. The performance of the models was evaluated using Root Mean Square Error (RMSE) and R^2 metrics. The ANFIS model provided higher performance than the MLP model due to the low level of error in predicting both livestock and agricultural production. | Utilization of advanced machine learning techniques for accurate food production prediction.  Consideration of key variables such as live animals, livestock yield, and agricultural losses in the prediction models. | Limitation in considering only time-series data for forecasts, neglecting external factors like climate and government policies.  Generalization of findings limited to Iranian data, potentially differing in data from other countries. |
| 17. | Food products pricing theory with application of machine learning and game theory approach. | Mobina Mousapour Mamoudan *et al.* (2021) | The research addresses the challenge of pricing perishable food products effectively by considering factors such as brand value, customer behaviour, and demand prediction. It aims to optimize pricing strategies to maximize product demand and profitability in the food industry. | The study employs a combination of machine learning techniques and a special type of Meta-Heuristic algorithm, specifically the CNN-LSTM-GA algorithm, and game theory models to develop a pricing strategy. The CNN-LSTM-GA algorithm is used for forecasting step prices, while the game theory model is applied to a 2-echelon green supply chain scenario with a supplier and two retailers. | Identified significant factors influencing food pricing, including brand value, product price, corruption, and demand rate.  Developed a pricing model using the CNN-LSTM-GA algorithm and game theory approach to optimize pricing strategies.  Validated the proposed method by comparing it with other deep learning models.  Demonstrated the applicability of the model for perishable food pricing in factories and periodic goods. | Integration of machine learning and game theory provides a comprehensive approach to pricing strategy.  Consideration of brand value and customer behaviour enhances the model's accuracy in predicting demand and setting optimal prices.  The model can serve as a decision support system for managers in the food industry to make informed pricing decisions. | The study focuses on perishable food products and periodic goods, limiting the generalizability of the model to other industries.  The complexity of the CNN-LSTM-GA algorithm and game theory models may require specialized expertise for implementation and interpretation. |
| 18. | An extrapolative model for price prediction of crops using hybrid ensemble learning techniques. | G.Murugesan and B. Radha (2021) | The study addresses the challenge of accurately predicting crop prices to assist farmers in making informed decisions about their agricultural commodities. | A hybrid ensemble learning technique that combines the ARIMA model with Support Vector Regression (SVR) to predict crop prices linearly. The SVR is applied to the ARIMA model's linear residuals, and the final prediction is made by combining the predictions from ARIMA and SVR. | The hybrid ensemble model shows promising results in predicting crop prices, providing a more accurate forecast compared to individual models. The approach effectively combines the strengths of both ARIMA and SVR to enhance prediction performance. | The model leverages the strengths of both ARIMA and SVR, leading to improved prediction accuracy and considers both linear and non-linear aspects of the data, enhancing its predictive capabilities.  Provides valuable insights into the application of hybrid ensemble learning techniques in agricultural price prediction. | The study may benefit from further validation and testing on a larger and more diverse dataset to assess the model's robustness.  The computational complexity of the hybrid ensemble model could be a potential limitation for real-time applications. |
| 19. | Artificial Neural Network Model for Predicting Maize Prices in Kenya | Wamalwa and Muchemi (2020) | The study addresses the need for an intelligent predictive tool for future maize prices in Kenya, highlighting the importance of adopting artificial intelligence (AI) in agricultural policy formulation. Existing tools lack predictive mechanisms and fail to provide actual figures of future maize prices, leading to subjective decision-making based on experience, technical, and fundamental analysis. | The study utilized exploratory and applied research to develop an artificial intelligence tool based on an ANN model for maize price forecasting. Data collection involved secondary data from FAO and Knoema websites, with model development following the CRISP-DM methodology. The ANN model was designed with input neurons capturing independent variables, hidden layers with varying neuron configurations, and output neurons for prediction. | The ANN model surpassed baseline linear models in maize price prediction accuracy, with a lower RMSE of 2.97 and MAD of 2.36. Optimal configurations of hidden neurons were determined for both univariate and multivariate modes, with the multivariate mode exhibiting superior performance based on MAD. | Demonstrates the effectiveness of ANN models in predicting maize prices in Kenya.  Provides a comprehensive methodology for developing and evaluating AI tools for agricultural forecasting.  Identifies optimal model configurations for improved accuracy in maize price prediction. | Limited discussion on the generalizability of the ANN model to other agricultural commodities.  Lack of detailed analysis on the interpretability of the ANN model results for stakeholders in the agricultural sector. |
| 20. | Long Short-Term Memory Model Based Agriculture Commodity Price Prediction Application | Chen Zhi Yuan (2020) | The paper addresses the challenges faced by farmers in maximizing profits due to factors like lack of experience and price instability in the agriculture industry. | The study proposes a software application with price forecasting features using machine learning algorithms such as ARIMA, LSTM, SVR, Prophet, and XGBoost. An experiment is conducted to identify the most optimal algorithm, with LSTM being chosen as the key model. | LSTM is proven to be the most accurate and efficient algorithm for handling complex data, showing great potential in forecasting future agriculture prices. The software also includes weather information, agriculture news, and a platform for farmers' trading. | LSTM algorithm is effective in handling increasing data complexity.  The software provides crucial information to assist farmers in making informed decisions.  Collaboration with third-party suppliers enhances trading opportunities for farmers. | The study does not delve into the specific challenges faced by farmers in different regions.  Limited discussion on the scalability and generalizability of the software application. |

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# RESEARCH METHODOLOGY

## 3.1 Data Collection and Analysis

Data collection and analysis are foundational components of food price forecasting using machine learning algorithms. The process of building an accurate and reliable predictive model begins with the collection of high-quality data, followed by thorough analysis. These steps are critical for ensuring that the model can make accurate predictions about food prices in Nigeria.

The initial step in data collection for food price forecasting involves identifying relevant data sources. For this project, the primary dataset is collected by the World Food Programme and includes comprehensive information about food prices in Nigeria. This dataset spans multiple years and encompasses various commodities and markets, providing a broad view of food price trends across the country. The dataset contains key information such as date, location, commodity type, unit of measurement, price in Naira, and price in USD, allowing for detailed analysis of food price dynamics over time and across different regions. The dataset contains 68,487 entries and 14 columns. It records food prices in various markets across Nigeria from 2002 to 2024. The columns include:

* **date**: The date of the price record.
* **admin1**: The first administrative division (state).
* **admin2**: The second administrative division (local government area).
* **market**: The name of the market.
* **latitude**: The latitude of the market location.
* **longitude**: The longitude of the market location.
* **category**: The category of the commodity (e.g., cereals and tubers).
* **commodity**: The specific commodity (e.g., Maize, Millet).
* **unit**: The unit of measurement (e.g., KG).
* **priceflag**: Indicates whether the price is actual or estimated.
* **pricetype**: The type of price (e.g., Wholesale, Retail).
* **currency**: The currency of the price (e.g., NGN for Nigerian Naira).
* **price**: The price of the commodity in the local currency.
* **usdprice**: The price of the commodity in USD.

After acquiring the dataset from the Humanitarian Data Exchange (Humdata.com), an initial examination is conducted to assess its quality and completeness. The dataset is found to be robust, with no missing or null values. However, it includes 24 different units of measurement, reflecting both wholesale and retail prices for different food commodities. This variability in units could potentially impact the performance of machine learning models if not addressed properly. To ensure consistency, all prices are standardized to common units such as kilograms and litres. This involves converting all measurements to these units, which helps in maintaining uniformity across the dataset.

Additionally, the dataset is separated into wholesale and retail prices by creating distinct columns for each or by adding a new feature that indicates the price type. Categorical columns such as 'Category' and 'admin1' are one-hot encoded to transform them into a format suitable for machine learning algorithms. Feature normalization is also performed on the prices to ensure that the scale does not impact the performance of the models. These preprocessing steps are crucial to prepare the dataset for subsequent analysis and model training.

Feature selection is an essential part of the analysis process, aimed at identifying the most relevant features for accurate food price forecasting. Among the various features in the dataset, the date and price are prioritized for their significant impact on the forecasting process. By focusing on these key variables, the dimensionality of the dataset is reduced, improving model interpretability and reducing computational complexity. Other relevant features may include the type of commodity, location, and market conditions, which are also considered during the feature selection process.

Machine learning algorithms such as neural networks, and statistical algorithms are employed to analyze the dataset and identify patterns and relationships between variables. These algorithms are capable of learning from historical data to make predictions about future food prices. The effectiveness of these models depends on their ability to capture the underlying trends and variations in the data.

To evaluate the accuracy and reliability of the predictive models, it is essential to validate them using independent datasets. This involves testing the models on data that was not used during the training phase to ensure that they are generalizable to new data. Cross-validation techniques are employed to split the data into training and testing sets and to validate the models using multiple iterations. This process helps in assessing the performance of different models and selecting the best one for the task.

Comparing the forecasting accuracy of different models is a critical aspect of this study. Each model is evaluated based on its predictive performance, using metrics such as mean absolute error (MAE), root mean square error (RMSE), and R-squared. These metrics provide insights into how well the models can predict food prices and help in identifying the most effective deployment model.

In summary, the data collection and analysis process for food price forecasting in Nigeria involves several steps: identifying relevant data sources, preprocessing the data to ensure consistency and quality, selecting pertinent features, and employing machine learning algorithms to build predictive models. The validation of these models using independent datasets ensures their accuracy and reliability. By comparing the performance of different models, the most suitable approach for forecasting food prices can be identified, contributing to more informed decision-making and improved food security in Nigeria. This detailed approach sets the stage for the next section, where the focus will be on the methodologies and techniques used for time series forecasting

**3.2 Price Time Series Forecasting Models**

Price time series forecasting models are a type of machine learning and statistical model that analyzes historical data to predict future price movements. These models are particularly useful in various economic and financial settings, including stock markets, commodities trading, and agricultural pricing, to assist stakeholders in making more informed decisions. There are several types of price time series forecasting models, each with its strengths and weaknesses. In this project, Prophet, Convolutional Neural Network-Recurrent Neural Network (CNN-RNN), and Long Short-Term Memory (LSTM) models were utilized and compared to determine which model achieved the highest accuracy rate.

Prophet

Prophet is an open-source forecasting tool developed by Facebook designed to handle time series data with strong seasonal effects and several seasons of historical data. It is particularly useful for its robustness to missing data and its ability to handle outliers well. The key features of Prophet include:

Trend Analysis: Prophet decomposes time series into three main components: trend, seasonality, and holidays. It uses piecewise linear or logistic growth curves to model the trend component.

Seasonality: Prophet can model daily, weekly, and yearly seasonal patterns. It also allows for the inclusion of custom seasonalities to capture periodic fluctuations in the data.

Holidays and Events: Prophet allows users to include the effects of holidays and special events, which can significantly impact price movements.

Model Interpretability: The model parameters are interpretable, making it easier for users to understand and trust the forecasts.

Prophet's flexibility and ease of use make it an attractive option for time series forecasting, especially in scenarios where the data exhibit complex seasonal patterns and are subject to sudden changes due to external events.

Convolutional Neural Network-Recurrent Neural Network (CNN-RNN)

The combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) leverages the strengths of both architectures to enhance time series forecasting. CNN-RNN models are particularly effective in capturing both spatial and temporal dependencies in the data.

CNN Component: The CNN part of the model is used for feature extraction. It processes the input time series data to identify local patterns and trends. CNNs are known for handling high-dimensional data and detecting complex structures.

RNN Component: The RNN, particularly the Long Short-Term Memory (LSTM) variant, is used to capture the temporal dependencies and sequential nature of the data. RNNs are well-suited for time series forecasting because they can retain information from previous time steps, making them capable of modelling long-term dependencies.

Combined Architecture: By integrating CNNs and RNNs, the model can effectively learn both spatial features and temporal patterns. This combined approach enhances the model's ability to predict future values accurately, especially in datasets with intricate patterns and dependencies.

CNN-RNN models are powerful for time series forecasting tasks where the data exhibit both local and global patterns. Their ability to handle complex data structures makes them suitable for a wide range of applications, including price forecasting.

Long Short-Term Memory (LSTM)

LSTM is a specialized type of RNN designed to overcome the limitations of traditional RNNs, particularly the problem of vanishing gradients. LSTM networks are capable of learning long-term dependencies in sequential data, making them highly effective for time series forecasting.

Memory Cells: LSTM networks use memory cells to store information over long periods. Each cell has three gates: input, forget, and output gates, which control the flow of information into and out of the cell. This gating mechanism allows LSTM networks to retain relevant information and forget irrelevant data.

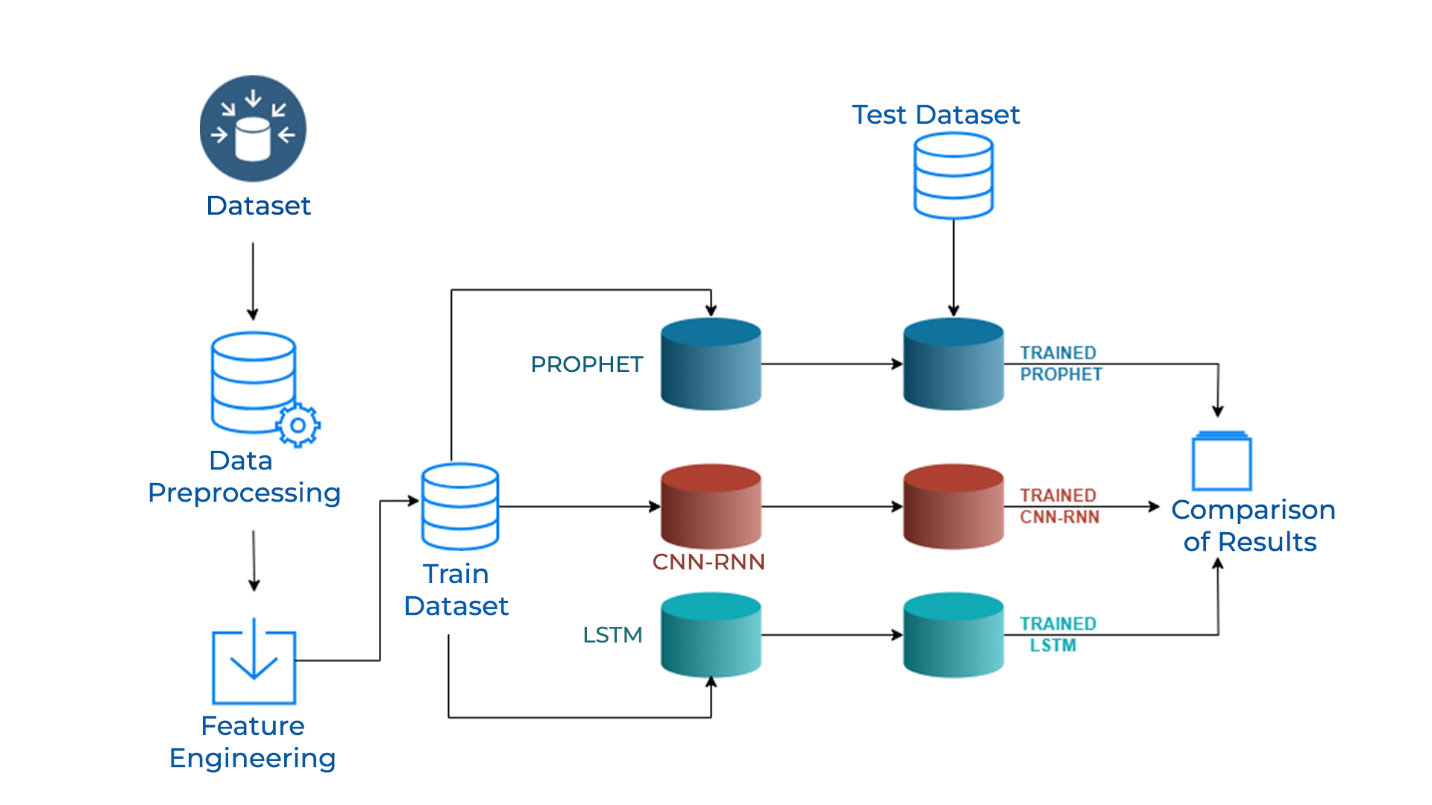
Handling Sequential Data: LSTM networks are specifically designed to process and predict data where the order of observations is crucial. They can capture complex temporal dependencies and are robust to varying sequence lengths.

Model Flexibility: LSTM networks can be combined with other neural network architectures, such as CNNs, to further enhance their predictive capabilities. This flexibility makes LSTM networks versatile for a wide range of time series forecasting tasks.

LSTM networks are particularly well-suited for time series data with long-term dependencies and are capable of providing highly accurate forecasts. Their ability to handle noisy and non-stationary data further enhances their applicability to real-world forecasting problems.

## 3.3 System Workflow

The system architecture of the food price forecasting project in Nigeria aims to design a robust framework that can effectively predict future food prices using a variety of advanced machine learning models. This architecture ensures the accurate prediction of food prices by leveraging different models and comparing their performance. The workflow of our project is presented in Figure 3.1.

Figure 3.1: *System Workflow*

#### 3.3.1 System Workflow Description

The overall system architecture involves several key stages:

1. Dataset Collection: The first step involves gathering relevant data, which includes historical food prices and other auxiliary data that might influence food prices, such as units, market demand, and socio-economic factors.
2. Data Preprocessing: This stage involves cleaning and organizing the collected data to make it suitable for analysis. Data preprocessing steps include handling missing values, normalizing the data, and transforming it into the required format.
3. Feature Engineering: In this step, relevant features are extracted and created to enhance the model's predictive power. Feature engineering involves selecting and creating variables that are most likely to influence food prices.
4. Model Training: The preprocessed and feature-engineered data is then split into training and testing datasets. Multiple models are trained on the training dataset, including:

* PROPHET: A model specifically designed for time series forecasting that handles seasonality and holidays well.
* CNN-RNN: A hybrid model that combines Convolutional Neural Networks (CNN) to capture local patterns and Recurrent Neural Networks (RNN) to model temporal dependencies.
* LSTM: Long Short-Term Memory networks, a type of RNN that is effective in capturing long-term dependencies in sequential data.

1. Model Evaluation: The trained models are evaluated on the testing dataset to assess their forecasting accuracy. Various performance metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared are used to compare the models.
2. Comparison of Results: The performance of different models is compared to identify the most accurate and reliable model for food price forecasting. This comparison helps in selecting the best model that can be deployed for real-time forecasting.

The workflow diagram in Figure 3.1 illustrates these stages, showing the flow from dataset collection to the final comparison of results. By following this architecture, the system ensures a comprehensive approach to food price forecasting, leveraging the strengths of different machine learning models to achieve the most accurate predictions.

## 3.4 Algorithms and Models

**3.4.1 Prophet**

Prophet is an open-source forecasting tool developed by Facebook's Core Data Science team. It is specifically designed to handle time series data and is capable of modelling trends, seasonality, and holidays to make accurate predictions. Prophet is particularly useful for datasets with strong seasonal effects and multiple seasonality with daily, weekly, and yearly cycles. Unlike traditional time series models, Prophet is robust to missing data and shifts in the trend, making it an excellent choice for real-world scenarios.

Prophet uses an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, along with holiday effects. The tool is designed to be easy to use and to produce forecasts that are flexible and interpretable. It works best with time series that have strong seasonality and several seasons of historical data.

Prophet can be considered a nonlinear regression model of the form

**𝑦𝑡=𝑔(𝑡)+𝑠(𝑡)+ℎ(𝑡)+𝜀𝑡,**

Where **𝑔(𝑡)** describes a piecewise-linear trend (or “growth term”),

**𝑠(𝑡)** describes the various seasonal patterns,

**ℎ(𝑡)** captures the holiday effects, and

**𝜀𝑡** is a white noise error term.

* The piecewise linear trend's knots (or change points) are automatically selected if not explicitly specified. Optionally, a logistic function can be used to set an upper bound on the trend.
* The seasonal component consists of Fourier terms of the relevant periods. By default, order 10 is used for annual seasonality and order 3 is used for weekly seasonality.
* Holiday effects are added as simple dummy variables.
* The model is estimated using a Bayesian approach to allow for automatic selection of the change points and other model characteristics.

In Python, Prophet can be implemented using the *prophet* library. Below is a step-by-step guide on how to perform forecasting using Prophet:

Step-by-Step Guide on Using Prophet

1. Install Prophet: First, ensure that you have the prophet library installed.
2. Load the Data: Load the time series dataset into Python. The data should be in a Pandas DataFrame with two columns: ds for the date/time column and y for the value you want to forecast.
3. Split the data: Split the dataset into training and testing sets using the train\_test\_split() function. This ensures that the model is trained on a subset of the data and evaluated on the remaining data.
4. Preprocess the Data: Ensure the data is clean and properly formatted. The ds column should be in datetime format, and there should be no missing values in the y column.
5. Create the Prophet Model: Create an instance of the Prophet model. You can specify additional parameters such as seasonality modes and holidays if necessary.
6. Fit the Model: Fit the Prophet model to your data using the fit() function.
7. Make Predictions: To make future predictions, you need to create a data frame containing the dates for which you want to predict values. Use the make\_future\_dataframe() function to generate this DataFrame and then make predictions using the predict() function.
8. Evaluate the Model: Prophet provides various diagnostics and plotting functions to evaluate the model's performance. You can visualize the forecast, the components (trend, seasonality), and the fit to historical data.
9. Additional Features: Prophet allows for the inclusion of additional regressors, custom seasonalities, and holiday effects to improve the forecast's accuracy.

By following these steps, you can effectively use Prophet to make time series forecasts. Prophet's strength lies in its ability to automatically handle complex seasonality and holiday effects, making it a powerful tool for time series forecasting in various fields such as finance, logistics, and marketing.

**3.4.2 Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN)**

Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are two powerful types of neural networks that can be combined to leverage their respective strengths for time series forecasting. CNNs excel at capturing spatial hierarchies and local patterns in data, while RNNs are designed to handle sequential data, making them suitable for time series analysis. This combination allows for more comprehensive modelling of temporal dependencies and patterns in time series data.

**Convolutional Neural Networks (CNN)**

CNNs are primarily used for processing data with a grid-like topology, such as images. They consist of convolutional layers that apply filters to the input data to detect local patterns. In general, the length of the output follows,

**Output size = ,**

where nx is the length of the input signal and nh is the length of the filter.

 In the context of time series forecasting, CNNs can be used to capture local trends and patterns over time by applying 1D convolutions.

1. Data Preparation: Before applying CNNs, the time series data must be prepared. This includes cleaning, preprocessing, and transforming the data into a format suitable for convolution operations. The data is typically divided into fixed-size windows or segments, which serve as the input to the CNN.
2. Splitting Data: The second step is splitting data as data needs to be split into training and testing sets. This is important to evaluate the performance of the model on unseen data. A 70:30 split is used for training and testing.
3. Feature Extraction: CNN layers apply multiple filters to the input data to extract features. Each filter performs a convolution operation, sliding over the data to produce feature maps. These feature maps capture different aspects of the local patterns in the time series data.
4. Pooling and Flattening: Pooling layers are often used to reduce the dimensionality of the feature maps, retaining the most important information while reducing computational complexity. After convolution and pooling, the feature maps are flattened into a single vector, which can be fed into a subsequent neural network layer, such as an RNN.

**Recurrent Neural Networks (RNN)**

By feeding historical sequences into the RNN, it learns to capture patterns and dependencies in the data. The process usually involves forward propagation to compute predictions and backward propagation to update the model's weights using optimization algorithms like Stochastic Gradient Descent (SGD) or Adam.

1. Combining CNN and RNN: By combining CNNs with RNNs, we can leverage the strengths of both architectures. CNNs can be used to extract local patterns from time series data, which are then passed to RNN layers to model temporal dependencies. This hybrid approach allows for a more comprehensive analysis of time series data, capturing both local and long-term patterns.

In Python, the Keras library provides tools for building and training CNN-RNN models. The Sequential API can be used to stack CNN and RNN layers, followed by a dense layer for the final output. Data is first passed through convolutional and pooling layers, and the resulting feature maps are fed into an RNN.

1. Model Training and Evaluation: The CNN-RNN model is trained on the prepared time series data using backpropagation through time. The model's performance can be evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared. Cross-validation can also be employed to assess the model's generalization ability.
2. Hyperparameter Tuning: Hyperparameters such as the number of convolutional filters, kernel size, number of RNN units, and learning rate must be carefully tuned to optimize the model's performance. Grid search or random search methods can be used to explore different hyperparameter combinations.
3. Model Deployment: Once the CNN-RNN model is trained and evaluated, it can be deployed for forecasting future time series data. This involves applying the same preprocessing steps to new data and using the trained model to make predictions.

**3.4.3 Long Short-Term Memory Networks (LSTM)**

Long Short-Term Memory (LSTM) networks are a special type of RNN designed to overcome the limitations of standard RNNs, particularly in capturing long-term dependencies in sequential data. LSTMs are highly effective in time series forecasting due to their ability to retain and utilize information over extended periods.

LSTM networks introduce memory cells that can maintain their state over long sequences. They use three types of gates—input, forget, and output gates—to control the flow of information into and out of the memory cells. This gating mechanism allows LSTMs to capture long-term dependencies and mitigate issues like vanishing gradients. The equations for the gates in LSTM are:

where, represents the input gate

represents forget gate

represents output gate

𝝈 represents the sigmoid function

represents weight for the respective gate(x) neurons

represents the output of the previous lstm block (at timestamp t - 1)

represents input at the current timestamp

bx represents biases for the respective gates (x).

The first equation is for the Input Gate which tells us what new information we’re going to store in the cell state. The second is for the Forget gate which tells the information to throw away from the cell state. The third one is for the Output gate which is used to provide the activation to the final output of the lstm block at timestamp ‘t’.

Knowing this, the equations for the cell state, candidate cell state and the final output are

where, represents cell state (memory) at timestamp (t) and represents candidate for cell state at timestamp (t).

note: \* represents the element-wise multiplication of the vectors.

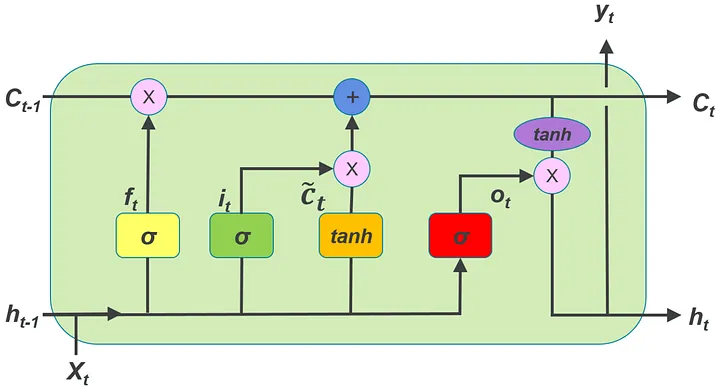


Figure 3.2 A block of LSTM at any timestamp {t} (Divyanshu, 2018)

1. Data Preparation: Similar to other models, data preparation for LSTMs involves cleaning, preprocessing, and formatting the time series data. The data is typically divided into sequences, where each sequence consists of a fixed number of time steps. These sequences serve as the input to the LSTM model.
2. Splitting Data: The second step is splitting of data as data needs to be split into training and testing sets. This is important to evaluate the performance of the model on unseen data. A 70:30 split is used for training and testing.
3. Feature Scaling: LSTMs require that the data be standardized or normalized to ensure that all features have the same scale. This step is crucial for improving the convergence and performance of the model.
4. Model Training: The LSTM model is trained using backpropagation through time. The network learns to adjust the weights and biases based on the errors between the predicted and actual values. The loss function, such as Mean Squared Error (MSE), guides the optimization process.
5. Implementation in Python: In Python, the Keras library offers a straightforward way to implement LSTM models. The Sequential API can be used to define the model, adding LSTM layers followed by dense layers for the output. The fit method is used to train the model on the training data, and the prediction method is used for making forecasts.
6. Hyperparameter Tuning: Tuning hyperparameters such as the number of LSTM units, the number of layers, learning rate, and batch size is critical for optimizing the model's performance. Techniques like grid search, random search, or Bayesian optimization can be employed to find the best hyperparameter settings.
7. Model Evaluation: The performance of the LSTM model can be evaluated using metrics such as MAE, RMSE, and R-squared. Cross-validation can also be used to assess the model's ability to generalize to new data. Plotting the predicted values against the actual values can provide a visual representation of the model's accuracy.
8. Model Deployment: Once the LSTM model is trained and evaluated, it can be deployed to forecast future values in the time series. This involves preprocessing new data using the same steps as during training and applying the trained model to make predictions.

## 3.5 Metrics

### 3.5.1 RMSE (Root Mean Squared Error)

Root Mean Squared Error (RMSE) measures the square root of the average of the squared differences between predicted and actual values. It senses how far the predictions are from the actual values.

### 3.5.2 MAE (Mean Absolute Error)

Mean Absolute Error (MAE) measures the average of the absolute differences between predicted and actual values. It measures the average magnitude of the errors in a set of predictions.

#### 3.5.3 (Coefficient of Determination)

The coefficient of Determination indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. An R² of 1 indicates that the regression predictions perfectly fit the data.

RMSE measures the square root of the average of squared differences between predicted and actual values, providing a sense of prediction errors. MAE calculates the average of absolute differences between predicted and actual values, offering a straightforward interpretation of average error magnitude. R² evaluates the proportion of variance in the dependent variable predictable from the independent variables, with values closer to 1 indicating better model fit. These metrics help validate the predictive model's accuracy in real-world applications, ensuring it minimizes error magnitudes and explains significant variance in food prices.

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IMPLEMENTATION AND RESULTS

## 4.1 Implementation Environment

The implementation of student academic performance prediction utilized Jupyter and Visual Studio Code (2023) as the development environments, with Python 3.11.3 as the programming language. The evaluation of model performance was conducted using linear regression metrics, including RMSE, MSE, and R-Squared.

## 4.2 Implementation Stage

The implementation stage shows the process of model training and testing on the Jupyter environment with a brief explanation of each step.

### 4.2.1 Presentation of Data

Here the attributes used in the dataset are gender, age, study time, failures, health, attendance, and academic scores.

### 4.2.2 Descriptive Analysis

It is a fundamental method used in data analysis to summarize and describe the main features of a dataset.

Table 4.2 provides summary measures that describe the central tendency, dispersion, and distribution of the data. For each variable/column in the dataset, the table includes the following statistics:

1. Count: The

### 4.2.3 Correlation of Data

Correlation is a statistical measure that quantifies the relationship between two variables. It indicates the strength and direction of the association between the variables.

Figure 4.2: Visualization of each attribute prior to gender

### 4.3 Linear Regression Analysis

In this section, we will construct a linear regression model to predict academic scores. The dependent variable (Y) is the academic score (G3), while the independent variables (X) include age, gender, study time, failures, health, attendance,

### 4.5 Results

In the linear regression scatter plot, the actual values (also called the observed values or ground truth) are represented on the vertical (x-axis), while the corresponding predicted values from the model are represented on the horizontal (y-axis). Each data point in the scatter plot represents an individual data instance in the dataset.

The red line in the scatter plot represents the regression line, which is the line of best fit determined by the linear regression model.

### 4.5.1 Deploying the Model for Prediction

After developing the machine learning model, I deployed it on a web page to make it accessible to students and individuals in the educational sector. The deployment process involved saving the model from a Jupyter Notebook using Pickle, a Python library for object serialization, and utilizing Flask, a Python web framework, as the backend to import and serve the model.

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SUMMARY AND RECOMMENDATION

## 5.1 Summary Research

Research on food price forecasting in Nigeria has garnered significant attention in recent years. These efforts combine the power of advanced forecasting techniques and machine learning models to provide timely and accurate predictions of food prices. Several studies have been conducted in this field, aiming to improve food security, enhance market stability, and support policy-making decisions.

The research typically involves developing and implementing sophisticated models that predict future food prices based on historical data and various influencing factors. These systems leverage machine learning algorithms to analyze the collected data and forecast the prices of key food commodities.

The literature review reveals that various machine learning algorithms have been employed in these systems, including Prophet, Convolutional Neural Networks combined with Recurrent Neural Networks (CNN-RNN), and Long Short-Term Memory networks (LSTM). Feature selection and extraction techniques are often applied to identify the most relevant predictors for food price forecasting. Furthermore, explainable AI techniques have been utilized to provide transparent and interpretable predictions, enabling stakeholders to understand the reasoning behind the model's forecasts.

The studies have demonstrated promising results in food price forecasting, with high accuracy rates achieved for predicting the prices of staples such as rice, maize, and yams. The implementation of these models has shown potential in early detection of price surges, risk assessment, and strategic planning for food distribution. Additionally, the predictive aspect of these systems has allowed for proactive measures to stabilize food markets, facilitating timely interventions and reducing the impact of price volatility on consumers.

While the research highlights the benefits of advanced food price forecasting models, there are still challenges to address. These include ensuring data quality and consistency, integrating the forecasting systems with existing market infrastructure, and addressing technical limitations such as model interpretability and computational efficiency.

In conclusion, the research conducted on food price forecasting in Nigeria demonstrates the potential of advanced machine learning models to transform market analysis and improve food security. These systems leverage cutting-edge techniques to enable accurate price predictions and informed decision-making. Further research and development are needed to address the challenges and optimize the performance and usability of these systems in real-world market settings.

## 5.2       Contribution to Knowledge

The use of machine learning in predicting food prices in Nigeria contributes to our understanding of the complex factors influencing market dynamics and enables more targeted interventions and support systems for food security.

Therefore, the contributions of this research work include:

Utilization of Nigerian Data for Various Food Commodities: This study leverages an extensive dataset specific to Nigeria, encompassing a range of food commodities. By using localized data, the research ensures that the models are tailored to the unique market conditions and agricultural practices in Nigeria, enhancing the relevance and applicability of the findings.

Comparative Analysis of Forecasting Models: The research evaluates the forecasting accuracy of three advanced machine learning models—Prophet, CNN-RNN (Convolutional Neural Network - Recurrent Neural Network), and LSTM (Long Short-Term Memory). This comparative analysis provides valuable insights into the strengths and weaknesses of each model in the context of food price forecasting, offering a comprehensive understanding of their performance under different conditions. The use of CNN-RNN and LSTM models represents a significant advancement in the application of machine learning to time series forecasting. These models are particularly adept at capturing complex patterns and dependencies in sequential data, making them well-suited for predicting volatile food prices. By exploring the effectiveness of these models, the research contributes to the broader field of machine learning and its applications in agricultural economics.

Enhanced Forecasting Techniques for Policy and Decision-Making: By improving the accuracy of food price forecasts, this research provides a valuable tool for policymakers, farmers, and other stakeholders. Accurate predictions enable more effective planning and intervention strategies, helping to stabilize food markets and mitigate the impact of price volatility on consumers and producers alike. The findings from this research support initiatives aimed at ensuring food security in Nigeria. By identifying the most reliable forecasting methods, the study helps to enhance early warning systems and response mechanisms, thereby contributing to the resilience of the food supply chain.

Overall, this research advances the field of food price forecasting through the application of sophisticated machine learning models and provides practical benefits for managing food security in Nigeria.

## 5.3 Recommendation

This project showcases the potential of machine learning in forecasting food prices in Nigeria by comparing the accuracy of three models: Prophet, CNN-RNN, and LSTM. The findings and techniques presented here provide a strong basis for further exploration and application in related fields. With continued advancements and adaptations, this research can contribute to the development of effective agricultural data analysis tools and foster improvements in food price prediction outcomes.

REFERENCES

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APPENDIX

**Analysis and Machine Model**

# Student Academic Performance Prediction

1 IMPORTING/ INSTALLING PACKAGES

import numpy as np

import pandas as pd