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Leveraging Machine Learning Technology in Nigeria's Policies Towards Food Security and Agricultural Value Chain Development

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Abstract
The structural constraints that affect the food security and agricultural value chain in Nigeria such as post harvest losses, price volatility and poor market information systems remain unchanged. Machine learning (ML) provides new tools to predict yields, food insecurity, post-harvest management and food prices, but is not widely used in national policies. In this article, the authors review the literature on recent empirical studies that have used ML techniques like Random Forest, Artificial Neural Networks, Decision Trees, and Support Vector Machines to analyze Nigeria's agricultural and food-security data, and how those techniques can be used to support Nigerian food security and value chain policies. A tabulated review of related literature highlights the focus, weaknesses and remedial suggestions of six recent studies. The review concludes that ML models can achieve high predictive accuracy for yield, price, food-insecurity outcomes, but most studies are geographically constrained, methodologically segregated from policy processes and/or focus on a single value chain segment. The article places these results in the current policy framework in Nigeria, namely the National Agri-Food Systems Investment Plan and the National Agricultural Technology and Innovation Policy, and recommends the institutionalization of ML tools in the policy process. It ends with policy recommendations such as a national agricultural data infrastructure, ML-based early-warning systems and capacity-building for evidence-based policy-making.
Keywords: *Machine Learning; Artificial Intelligence; Food Security; Agricultural Value Chain; Nigeria; Policy; Predictive Analytics*

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I. Introduction

Despite the efforts made to promote food security in Nigeria, which is defined as the physical and economic access to enough, safe and nutritious food for all citizens at all times, the situation is still marred by various weaknesses along the entire agricultural value chain from production to processing, storage, distribution and marketing. Nigeria, with a population of over 220 million people, is expected to reach over 350 million by 2050, creating a high demand for food and putting pressure on the food system, which loses up to 40 percent of its output every year due to inefficiencies in food handling, storage and transport.

To overcome these inefficiencies, a new technology has been developed: machine learning (ML) is a subset of artificial intelligence (AI) that uses algorithms to learn patterns from data to make predictions or classifications without explicit programming for each task. In the world, ML methods like Random Forest, Artificial Neural Networks (ANN), Decision Trees and Support Vector Machines (SVM) have been used to predict crop yields, diagnose crop diseases, forecast food prices and identify households vulnerable to food insecurity. A number of empirical studies in Nigeria have started to use these techniques with local data, but the use of these studies in the development of national food security and value chain policy is still limited.

This article examines the food security and value chain policy landscape in Nigeria using the prism of machine learning technology. It summarizes the latest empirical studies that have used ML to address agricultural and food-security issues in Nigeria in tabular form and assesses the extent to which existing policy frameworks have integrated ML. Finally, the article makes recommendations for further policy action to institutionalize ML-driven decision-making in Nigeria's food security architecture.

Despite its significant contribution to the Gross Domestic Product (GDP) and employment of a large population in Nigeria, the agriculture sector has not proportionately contributed to food security. Structural weaknesses, such as smallholder production systems, poor storage and transportation facilities, lack of market information, and limited access to finance are still reducing the value that can be delivered to farmers and consumers. The use of digital technologies, and machine learning in particular, is increasingly being suggested as a way to overcome these shortcomings by enhancing the timeliness, granularity and accuracy of information for farmers, aggregators and policy makers.

II. Conceptual Framework: Machine Learning, Food Security and the Value Chain

Despite the efforts of the Nigerian government towards food security, which is the physical and economic availability of adequate, safe and nutritious food for all people at all times, the situation remains beset by a host of weaknesses across the entire agricultural value chain from production, processing, storage, distribution, and marketing. Nigeria has over 220 million people and will reach over 350 million by 2050 with a resulting high demand for food and strain on the food system, which suffers from up to 40 percent loss annually because of inefficient food handling, storage and transportation.

To address the inefficiencies these, enable, a new technology has emerged: machine learning (ML), a type of artificial intelligence (AI) that enables algorithms to discover patterns in data and then use those patterns to predict or classify in a way that doesn't require any explicit programming for each of the predictions or classifications. Various machine learning models have been employed to predict crop yields, identify crop diseases, forecast food prices, and determine households that are at risk of food insecurity in the world. In the World, ML models such as Random Forest, Artificial Neural Networks (ANN), Decision Trees, and Support Vector Machines (SVM) have been applied to forecast crop yields, diagnose crop diseases, forecast food prices and identify households that are at risk of food insecurity. A number of empirical studies in Nigeria have started to use these techniques with local data, but the use of these studies in the development of national food security and value chain policy is still limited.

The article reviews the policy landscape for food security and value chain in Nigeria with reference to machine learning technology. It provides a tabular summary of the most recent empirical studies employing ML for addressing challenges of agriculture and food security in Nigeria and evaluates the extent to which the policy frameworks have embraced ML. Lastly, recommendations are made for ongoing policy measures that will institutionalise the use of ML in decision making in Nigeria's food security architecture.

Although Agriculture has a large population in Nigeria that is employed and contributes enormously to Gross Domestic Product (GDP) in Nigeria, the sector has not come across proportionately to food security issues. Structural weaknesses, such as smallholder production systems, poor storage and transportation facilities, lack of market information, and limited access to finance are still reducing the value that can be delivered to farmers and consumers. Digital technologies and machine learning in particular, are increasingly proposed as a solution to these limitations to deliver farmers, aggregators and policy makers better, more timely and more granular and accurate information.

The four components of food security typically explored are: availability, access, utilization and stability. Each dimension is determined by the performance of the agricultural value chain, the chain of value adding activities that involve production, aggregation, processing, storage, transportation and marketing of raw agricultural production. Machine Learning applications fit into all the dimensions described above; predictive models can forecast production (availability), predict price shocks and vulnerability of households (access and stability) and identify quality or safety risks in processing and storage (utilization).

ML models can handle input data of vastly different dimensions and types, such as satellite imagery, weather data, market prices, household surveys, etc., and uncover relationships that cannot be expressed a priori analytically, such as non-linear relationships. This capability renders ML an ideal type of tool for a value chain as diverse and data-rich as Nigeria's, where a wide variation exists between agro-ecological zones, farm size and market access.

In literature studied in this article three general families of technique of ML are repeated. Supervised learning models such as Random Forest, Decision Trees, Support Vector Machines, and regression-based models are trained on labeled historical data to predict the results of interest like yield, price, and food-insecurity status. A more flexible class of supervised model, Artificial Neural Networks (ANN), can model complex, non-linear relationships between weather, soil and management variables, and have demonstrated good performance in yield-prediction studies conducted in Nigeria. In addition to these models, model-interpretability techniques such as SHapley Additive exPlanations (SHAP) values are also gaining traction to pinpoint which factors most strongly influence the outcome of the prediction (e.g., storage conditions, market distance), making predictions from ‘black boxes’ actionable policy insight.

III. Methodology

The approach used in this article is a documentary and analytical review method. Targeted searches were conducted using a combination of key words, including 'machine learning', 'artificial intelligence', 'food security', 'value chain' and 'Nigeria', to identify peer reviewed papers from journals, conference papers and policy documents published between 2022 and 2026. In Section 4, studies were chosen for the literature review based on the fact that they used a specific, identifiable machine learning technique on Nigerian agricultural, food-price or food-security data, and did not just talk about digital agriculture in conceptual terms.

The selected studies have been evaluated on the basis of the focus of the study, the method used, the limitations or shortcomings identified by the authors or from the study design, and the recommendations for correcting the limitations or shortcomings. The comparative assessment in Section 5 then involved reviewing Nigeria's key food security and value chain policy documents to determine how much they currently refer to or require data-driven and ML-based tools.

It is not a formal systematic review with pre-registered inclusion criteria, but rather a qualitative and synthetic review that focuses on analysing a manageable number of illustrative studies rather than on exhaustively summarising all publications in this rapidly expanding field. This approach aligns with the aim of the article, which is not to exhaustively list all the possible applications of ML in African agriculture, but to summarize the current situation of ML-policy integration in Nigeria in particular and to highlight the tangible and actionable gaps.

IV. Review of Related Literature

A tabulated review of six recent studies that have used machine learning techniques to address food security and agricultural value chain questions in Nigeria is provided in Table 1. Each entry briefly summarizes the authors, year of publication, title of the article, main focus of the article, shortfalls identified, and suggestions for addressing the shortfalls.

Table 1: Review of Related Literature on Machine Learning Applications to Food Security and Value Chain in Nigeria

Author(s) & Year	Title of Article	Main Focus	Shortfalls	Suggestions to Remedy Shortfalls
Villacis, Badruddoza, Mishra & Mayorga (2023)	The Role of Recall Periods When Predicting Food Insecurity: A Machine Learning Application in Nigeria	Uses ML classifiers on Nigeria LSMS-ISA panel data to test how the recall period used in food-insecurity surveys affects prediction accuracy.	Relies on self-reported experience-based indicators, which can be subjective; findings are not disaggregated by value chain stage.	Combine ML-based survey prediction with objective market and price data, and extend analysis to specific value chain segments.
Villacis, Mishra & Mayorga (2023)	Experience-Based Food Insecurity and Agricultural Productivity in Nigeria	Examines the statistical link between household agricultural productivity and experience-based food security outcomes using panel data.	Primarily econometric rather than a full ML pipeline; limited treatment of post-farm-gate (processing, storage, market) factors.	Incorporate ML-based yield and loss prediction models alongside the econometric analysis to capture value chain effects.
Samaila & Wycliffe (2025)	Machine Learning-Based Approaches to Improve Crop Yield Prediction in Agriculture in Adamawa State, Nigeria	Compares ANN, Decision Tree, and SVM models for predicting maize, sorghum, and groundnut yields using rainfall, temperature, and soil-moisture data.	Geographically limited to five Local Government Areas in one state; excludes market, price, and post-harvest variables.	Scale the modelling framework nationally and integrate market-access and storage variables to link yield prediction to food security policy.
Adediran, Onyegbula, Oyeyipo, Ahmed, Fashanu & Ariyo (2025)	Smart Postharvest Management: Leveraging AI for Reduced Food Loss, Waste, and Improved Quality	Reviews AI-driven monitoring technologies for reducing post-harvest food loss and improving produce quality across the supply chain.	Largely conceptual/review in nature; does not test a specific ML model on Nigerian field data or quantify cost of deployment for smallholders.	Pilot and empirically validate AI monitoring tools with smallholder cooperatives, and publish cost-benefit data to guide policy funding.
Bali, Ngida, Habila & Goni (2025)	Artificial Intelligence Applied in Optimization of Crop Yield for Ensuring Food Security in Nigeria: A Systematic Analysis	Systematically reviews AI applications, precision farming, disease detection, yield forecasting, supply chain optimisation, in Nigerian agriculture.	As a systematic review, it synthesises existing studies rather than generating new field evidence; notes infrastructure and data	Follow up the review with primary data collection and policy-linked pilot projects addressing the infrastructure

Author(s) & Year	Title of Article	Main Focus	Shortfalls	Suggestions to Remedy Shortfalls
			gaps but does not model solutions.	and data gaps identified.
Khan, Dar, Okechukwu, Hisam, Azad, Smerat & Farooque (2026)	Food Price Prediction in Nigeria: A Comparative Analysis of Linear Regression and Machine Learning Models	Compares Random Forest and regression models in forecasting Nigeria's Food Price Index using FAO subsector data from 1990-2025.	Uses aggregate national price indices, which mask sub-regional and commodity-specific price dynamics relevant to local policy design.	Extend the model to state- or market-level price data and integrate outputs into an early-warning system for policymakers.

All these studies show that ML models perform well on different value chain tasks: food-insecurity classification (with recall periods), agricultural productivity and welfare linkages, yield prediction with varying climatic conditions, monitoring post-harvest losses, and predicting food prices. A common missing element, however, is fragmentation: most studies focus on a single value chain node (production, price, household welfare) with geographically or methodologically limited data sets, and limited incorporation into a coherent and policy actionable value chain system. The fragmentation reflects the overall challenge to the Nigerian agricultural policy, as described in Section 4, where production-focused policies have been implemented ahead of investments in market integration, processing and data infrastructure.

V. Nigeria's Food Security and Value Chain Policy Landscape

5.1 National Agri-Food Systems Investment Plan (NASIP)

The third National Agriculture Investment Plan (NASIP) in Nigeria is a departure from the narrow production-based agriculture plans, and introduces a more comprehensive agri-food systems approach that covers production, processing, distribution and consumption. It is supported by investment framework worth of multi-trillions of naira, in line with the Kampala Declaration and home-grown initiatives like Nigeria Agenda 2050 and the National Development Plan, and is the most comprehensive investment vehicle available today for coordinated public and private investments in the value chain.

5.2 National Agricultural Technology and Innovation Policy (NATIP, 2022–2027)

Low productivity of smallholder farmers is a constraining factor on food availability and competitiveness of value chains and NATIP is working on strengthening agricultural research, extension services and uptake of technology. Its definition of 'innovation' is quite general, but there is less specificity on data science and machine learning infrastructure, including national agricultural datasets, computing capacity, or digital extension platforms, than there is on the potential of the technology.

5.3 Complementary Frameworks

While the National Policy on Food and Nutrition, the National Rice Development Strategy II, the National Livestock Growth Acceleration Strategy, and the Revised National Gender Policy on Agrifood Systems Transformation all touch on nutrition, commodity-specific development, and inclusion, no one of these policies has a systematic approach for using predictive analytics or ML-based monitoring in implementation or evaluation. These frameworks are summarised in Table 2, and their current level of machine learning and data integration is also assessed.

Table 2: Nigeria's Food Security and Value Chain Policies and Their Current Level of Machine Learning / Data Integration

Policy / Strategy	Period	Primary Focus	Current ML/Data Integration
National Agri-Food Systems Investment Plan (NASIP)	2026–2027	Coordinated public/private investment across production, processing, distribution, and consumption.	Low–Medium: references data-driven planning; no explicit ML mandate.
National Agricultural Technology and Innovation Policy (NATIP)	2022–2027	Research, extension services, and technology adoption to raise productivity.	Low: technology focus present, but ML/data-science

Policy / Strategy	Period	Primary Focus	Current ML/Data Integration
			infrastructure not specified.
National Policy on Food and Nutrition	2016–2025 (revised)	Diet quality, food-system transformation, nutrition in the first 1,000 days, food safety.	Low: monitoring largely survey-based; no predictive-analytics component.
National Rice Development Strategy II	2020–2030	Closing the domestic rice supply-demand gap through productivity and value addition.	Low: yield targets set administratively, not through predictive modelling.
National Livestock Growth Acceleration Strategy	2025–2035	Livestock productivity, disease control, and grazing-conflict mitigation.	Low: disease-surveillance data exists but is not yet linked to ML-based early warning.
Revised National Gender Policy on Agrifood Systems Transformation	2025–2030	Equitable access to land, credit, and decision-making for women in agriculture.	Low: gender-disaggregated data collected, but not used for predictive targeting.

As Table 2 indicates, Nigeria's food security and value chain policies are, at present, predominantly investment- and programme-oriented rather than data- or model-driven. This pattern is consistent with the fragmentation identified in the literature review: empirical ML research and national policy design currently operate largely in parallel, with limited formal channels connecting the two.

VI. Applications and Gaps in Deploying Machine Learning Across the Value Chain

Based on the literature reviewed, ML applications that are relevant to Nigeria's food security policy can be classified into four value chain functions:

- Production forecasting: ANN, Decision Tree and Random Forest models have been found to be highly accurate (R^2>0.9 for some state-level studies) for predicting staple crop yields based on rainfall, temperature and soil-moisture data, which can aid in early planning for input distribution and strategic reserves.
- Targeted infrastructure investment: Storage conditions, access to drying facilities and market distance are identified as important factors that drive post harvest loss, based on interpretability methods using the Random Forest model.
- Comparative modelling of Nigeria's Food Price Index indicates that Random Forest is better than linear regression for multi-month forecasting, providing a basis for early-warning systems on food-price inflation.
- Household food-insecurity prediction: ML classifiers trained on nationally representative household survey data can predict food-insecure households with 78–90 percent accuracy using short recall-period indicators, which can help target social protection programmes more timely.

Notwithstanding this potential, the studies reviewed show common structural gaps that also characterize the Nigeria value chain challenges: lack of an integrated national data infrastructure with more integrated datasets at the Ministry/Agency level; limited computing and connectivity infrastructure in rural areas where models would be implemented; limited technical capacity within relevant Ministries/Agencies to operationalize the outputs of the models; and weak linkages between the interface of research outputs and policy/budgetary decision making processes.

These gaps reinforce each other. The poor data quality and lack of data comprehensiveness reduces the accuracy and generalizability of models trained at state or zone level, and the confidence with which policy makers can act on model output at national scale. Limited connectivity in rural areas not only affects data collection but also the ability to get outputs of models back to farmers and local extension officers in a usable form, such as in the form of SMS-based advisories or dashboards that can be accessed on basic devices. Therefore, closing any one gap alone, such as funding a single yield-prediction pilot without making complementary investments in the

other dimensions, is unlikely to lead to sustained policy impact without complementary investments in the other dimensions.
The discussion will focus on the following questions: What are the implications of the evidence presented for developing evidence-based, ML-informed policies?

. This is a discussion on how to develop evidence-based, ML-informed policy.
The evidence reviewed indicates that machine learning is technically capable of supporting several core functions in the area of food security in Nigeria, while institutional readiness is lagging behind. There are existing frameworks, like NASIP and NATIP, that offer a starting point for integrating ML tools; both already emphasize data-driven planning and innovation. What is currently lacking is a clear directive (and the resources, information systems, and personnel needed to implement it) to make use of ML-derived forecasts and risk indicators in a regular manner as government policy tools, not as research projects.
To bridge this gap, coordinated action is needed at three levels: first, in building shared, interoperable agricultural and market data; second, in training within ministries and agencies to interpret and use the outputs of ML; and third, in formally incorporating ML-based indicators into food security planning, budgeting, and early-warning systems.

VII. Discussion: Towards Evidence-Based, ML-Informed Policy

The evidence presented indicated technical readiness for the use of machine learning to support the following key functions of food security in Nigeria, while institutional readiness remains limited. There are existing tools like NASIP and NATIP that provide an entry point for integrating ML tools, and both already give high priority to data-driven planning and innovation. There is a need for the government to make use of and test such forecasts and risk indicators, generated by ML, in its day-to-day policy making and decision making processes, and not just as research products.Whereas, what is still lacking is a mandate, accompanied by the budget, data infrastructure and human capacity, for government agencies to use and test the forecasts and risk indicators generated by ML in their routine operations.

There is a need for coordinated action at three levels: data (building shared, interoperable agricultural and market data); technical capacity (capacity building within ministries and agencies to interpret and use ML outputs); and institutional mandate (institutionalization of ML-based indicators in planning, budgeting, and early-warning systems on food security).

7.1 Institutional Readiness

Technical infrastructure is not the only factor that determines institutional readiness for ML adoption. It needs to be clear in government who owns data pipelines and model outputs, and standard operating procedures for turning predictions into administrative action (e.g., input distribution or enrolment in a safety net when a model identifies high food-insecurity risk), as well as ways to audit model performance over time. In the absence of these institutional components, even the most precise models may not be more than academic exercises.

7.2 Data Infrastructure and Governance

Some of the studies reviewed use data sets that were not developed to be utilized for timely policy purposes or are not directly connected to each other, such as the World Bank's Living Standards Measurement Study or FAO price indices, which are based on state level meteorological data. The cost of generating and maintaining ML models that inform policy decisions would be significantly reduced if there were a coordinated national agri-food data infrastructure, where standards were established for data collection, storage, and sharing between federal and state agencies, research institutions, and the private sector. This infrastructure should be supported by data-governance mechanisms that will preserve the anonymity of farming households and allow for data to be used for public interest analysis and analytics, while still being used responsibly.

7.3 Limitations of This Review

This article has relied on secondary data, derived from a documentary review of published literature, and public policy documents, rather than on primary data collection or development of original models. The literature reviewed here was illustrative of the current applications of ML in food security and value chain space in Nigeria but not exhaustive as new studies are likely to be published soon after this review. The analysis of policy documents shown in table 2 is based on the provisions as stated publicly and may not represent internal unpublished digitalisation projects undertaken by government agencies. These restrictions should be taken into account when implementing the article's recommendations and future research that involves primary data collection and policy process analysis will reinforce the evidence base.

7.4 Implications for Key Stakeholders

The results have specific implications for various actors in Nigeria's food system. Federal and state agricultural agencies face the challenge of scaling up ML research towards institutionalized decision-support systems that are part of the planning process. For research institutions and universities, a chance to bring the future of research more in line with policy-relevant issues such as sub-national price transmission or focused safety-net eligibility, instead of a methodological similarity across various geographies in terms of yield prediction exercises. The gap identified in this review suggests investments in shared data infrastructure and capacity building, instead of in single proprietary solutions that require ongoing government agency maintenance. The final beneficiaries of well-designed ML systems, smallholder farmers, will benefit if the system's predictive outputs are translated to local information that can be used to guide action: such as localised planting advice or early warnings of price shocks, for instance, rather than being caged in technical reports.Several of the studies reviewed rely on datasets, the World Bank's Living Standards Measurement Study, FAO price indices, state-level meteorological records, that were not originally designed for real-time policy use and are not consistently linked to one another. A coordinated national agri-food data infrastructure, with agreed standards for data collection, storage, and sharing across federal and state agencies, research institutions, and private-sector actors, would substantially lower the cost of developing and maintaining policy-relevant ML models. Such infrastructure must be accompanied by data-governance safeguards that protect the privacy of farming households while enabling responsible secondary use of data for public-interest analytics.

VIII. Conclusion and Recommendations for Further Policy Action

From yield forecasting to price forecasting and targeting vulnerable households, machine learning provides Nigeria with a workable toolbox for bolstering food security and value chain performance. The literature reviewed shows that there is a high technical feasibility, but also that there is a fragmented and not yet policy-integrated application. The following additional policy directions are recommended for taking this technical potential to the level of measurable food security gains:

- Create a national agri-food data infrastructure that integrates production, weather, market price and household survey data on a common platform that is interoperable, accessible to researchers and policymakers.
- Ensure the incorporation of ML-based early-warning indicators in the monitoring and evaluation systems of NASIP, NATIP and related strategies: food prices, post-harvest loss risk, household food insecurity.
- Invest in digital infrastructure in rural areas, such as connectivity and computing access, to facilitate the deployment of predictive tools on the field level, in addition to the physical infrastructure (storage and cold chains etc.).
- Develop technical capacity of Federal Ministry of Agriculture and Food Security and State agencies through planned training and collaboration with Universities and Data-Science institutions.
- Sponsor translation pilot schemes to take ML research from publication to operational decision support tools, with clear evaluation and scale-up pathways.
- Develop and apply ML models that can be used beyond individual value chain actors to integrated end-to-end models that incorporate production, storage, market and consumption data to capture the interdependencies of food security outcomes.
- Ensure robust data governance and ethical protections to maintain farmer and household privacy in the era of the growing collection and analysis of agricultural data.

Continued improvement will require the integration of machine learning as an institutionalised part of food security and value chain governance in Nigeria, with regular investments in data, infrastructure and human resources.

The policy directions above are not mutually exclusive, but rather complementary: a national data infrastructure is of little use if there is not a national mandate to implement the resulting indicators, and technical capacity-building is most effective when it is complemented by pilot programmes to provide staff with on-the-job training in how to operationalize model outputs into administrative decisions. Nigeria's current policy framework, which includes NASIP and NATIP, already has the strategic language of data-driven planning and innovation; all that is needed now is the intentional, funded and coordinated task of making machine learning a regular ingredient of the way food security and value chain policy is designed, monitored, and adapted over time.

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