



**Edun Joshua**  
**Mbuotidem Awak**  
**Makinde Kayode**

+

+

+

+

+



TACKLING POST-HARVEST LOSS  
WITH TECHNOLOGY





# **Post-Harvest Losses Problem: Reducing Post-Harvest Losses to Build Youth-Led Agri-Businesses**

Investigating Strategies to Mitigate PHL

**Edun Joshua**

**Mbuotidem Awak**

**Makinde Kayode**

**Organizers:** Data Community Africa, AgriConnect, Dicey Tech, REDtech  
Africa

*Academic report*

Lagos, May 2025



**Post-Harvest Losses Problem: Reducing Post-Harvest Losses to Build Youth-Led Agri-Businesses**

Copyright © 2025 - Edun Joshua, Mbuotidem Awak, Makinde Kayode; Data Community Africa.

This dissertation is original work, written solely for this purpose, and all the authors whose studies and publications contributed to it have been duly cited. Partial reproduction is allowed with acknowledgment of the author and reference to the year, institution - *Data Community Africa* - and public defense date.



# Acknowledgements

Our deepest thanks go to the **Data Community Africa** community. We attribute significant professional growth to the foundation and resources they consistently provide.

We are also immensely grateful to **REDTech** and DiceyTech **DiceyTech** for sponsoring valuable hackathons like this. They empower data enthusiasts by offering crucial opportunities to challenge themselves and showcase their abilities.



# Abstract

In Nigeria, millions of tons of food go to waste every year; not because of poor harvests, but because they never make it from farms to markets. To tackle these losses, we present Okra — a data-driven digital marketplace and logistics platform built to seamlessly connect farmers, buyers, and logistics providers in real time. Its stand-out feature is an AI-powered tool for predicting freshness and quantity of produce using image recognition, and helping buyers make faster, more informed decisions. Okra also uses data such as rainfall forecasts and harvest schedules to predict high-risk post-harvest loss periods, enabling early interventions like dispatching logistics or alerting farmers.

**Keywords:** Post Harvest Loss, Digital Marketplace, AI.



# Contents

<i>List of Figures</i>	xi
<i>List of Tables</i>	xiv
<b>1 Introduction</b>	<b>1</b>
1.1 Analysis of Post-Harvest Losses in Nigeria . . . . .	1
1.2 Impact on Youth and National Economy . . . . .	5
<b>2 Causes Of PHL</b>	<b>7</b>
2.1 Poor Transportation Infrastructure . . . . .	7
2.1.1 Key effects of poor transportation . . . . .	8
2.1.2 Inadequate Cold Storage and Processing . . . . .	8
2.1.3 Limited Market Access and Information . . . . .	9
2.1.4 Conclusion . . . . .	10
<b>3 Okra: Our Solution Proposal</b>	<b>12</b>
3.1 Core Concept and Functionality . . . . .	12
3.1.1 Marketplace Networking . . . . .	12
3.1.2 Logistics Integration . . . . .	12
3.1.3 AI-Powered Insights . . . . .	13
3.1.4 Youth-led Agribusiness Empowerment . . . . .	13
3.2 Screens . . . . .	14
3.3 Data Strategy . . . . .	15
3.3.1 Image Data Collection . . . . .	15
3.3.2 Data Labeling and Training . . . . .	15
3.3.3 Feedback Loop (Active Learning) . . . . .	15
3.4 Auxiliary data sources . . . . .	15
3.4.1 Privacy and Governance . . . . .	16
3.5 OkraAI . . . . .	16
3.5.1 Dataset . . . . .	16
3.6 Data Split . . . . .	17
3.7 Model Training . . . . .	17
3.8 Deployment . . . . .	17
3.9 Confusion Matrix . . . . .	18

3.10 Training Progression . . . . .	19
3.11 F1-Confidence Curve . . . . .	20
3.12 Deployment and Demo . . . . .	20
<i>Bibliography</i>	24



# List of Figures

1.1 PHL in Nigeria for key crops. Source: APHLIS database, 2019 . . . . .	2
1.2 PHL loss in the various steps in the maize value chain. Source: APHLIS database, 2019 . . . . .	3
1.3 PHL expressed in the percentage of the average person's annual dietary requirements . . . . .	3
1.4 Financial value of rice PHL loss in Nigeria from 2013 to 2020. Source: APHLIS database, 2019 . . . . .	5
3.1 Screenshot of the landing page . . . . .	14
3.2 Screenshot of the farmer's dashboard . . . . .	14
3.3 Screenshot of the buyers's dashboard . . . . .	14
3.4 Screenshot of the buyers's dashboard . . . . .	15
3.5 Confusion matrix of the model . . . . .	19
3.6 Training progression of the model . . . . .	19
3.7 F1-confidence curve of the model . . . . .	20
3.8 Gradio Demo of the model . . . . .	21



# List of Tables

1.1	Nutritional Impact of Maize Post-Harvest Losses in Nigeria, 2022 . . . . .	4
3.1	Class distribution before re-splitting . . . . .	17
3.2	Model performance on the validation set. . . . .	18



# 1

## Introduction

*Authors:* Edun Joshua, Mbuotidem Awak, Makinde Kayode

*License:* [LaTeX Project Public License v1.3c](#)

*Official Repository:* [GitHub Repository](#)

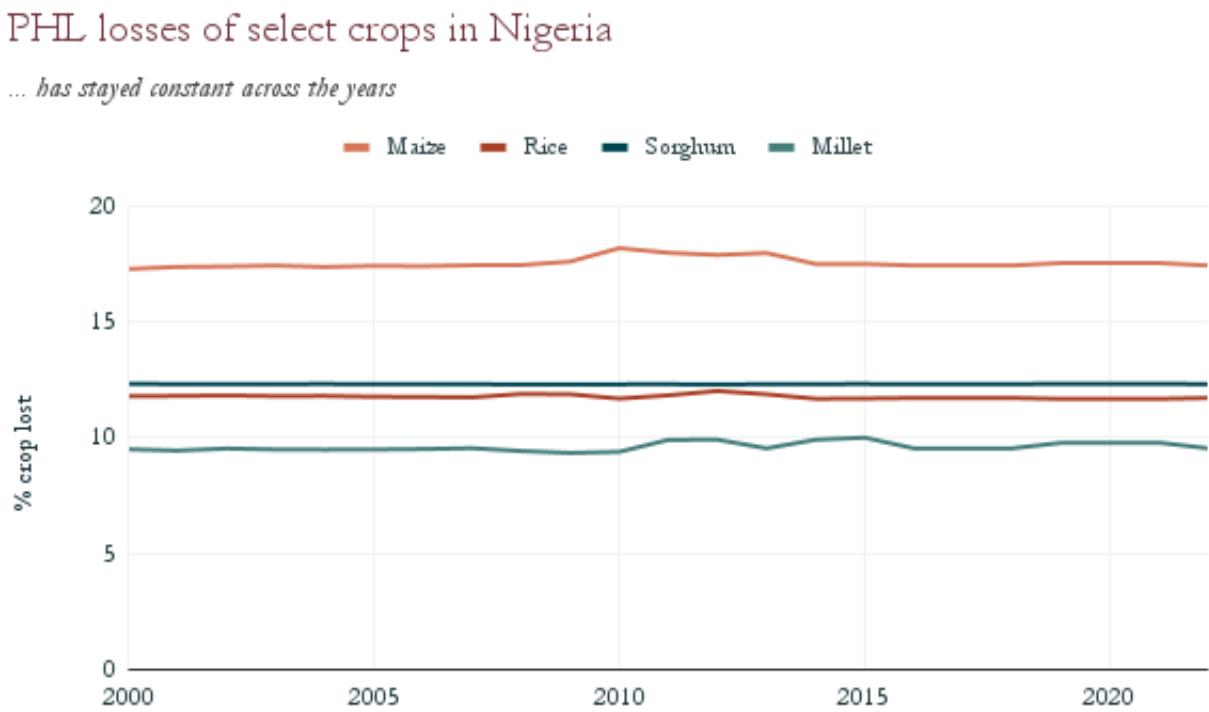
Post Harvest Losses (PHL) refers to the measurable reduction in the quantity or quality of food after harvest, making it unfit for consumption ([FAO, n.d.](#)). Globally, roughly one-third of food produced is lost or wasted. In Nigeria, the scope is especially alarming: studies estimate that the country loses on the order of 40–50% of its total food production each year.

### Note

*“Each year, Nigeria wastes 40% of its total food production”, equivalent to significant greenhouse gas emissions ([World Bank, 2020](#)).*

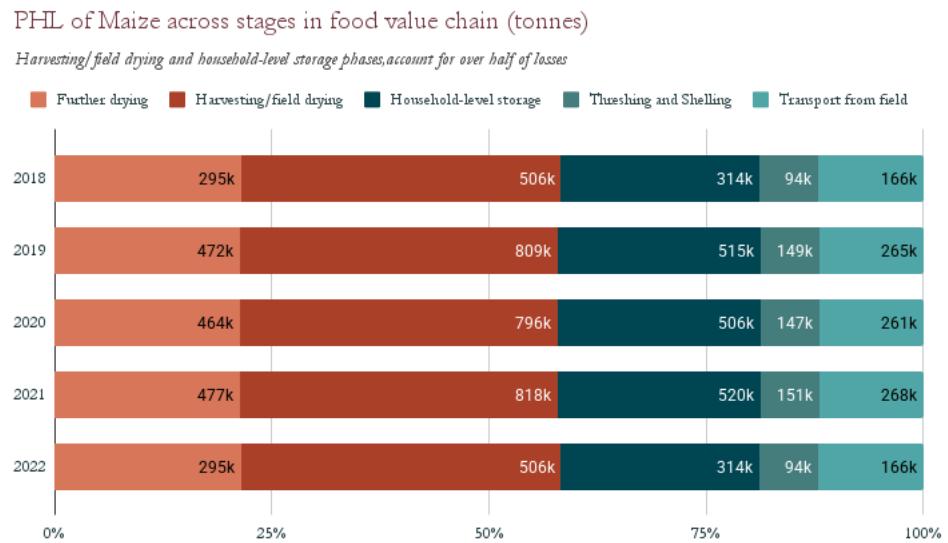
### 1.1 Analysis of Post-Harvest Losses in Nigeria

According to [Nigeria \(2024\)](#), FAO experts similarly report losses around 50% for certain crops. USAID reports that post-harvest losses for fresh produce in Nigeria can reach almost 50% [Udi \(2024\)](#), and for tubers, fruits, and vegetables, losses can range between 50% and 60% ([Okojie et al., 2024](#)). These statistics reveal a gap between Nigeria’s agricultural output and what actually reaches consumers. [Figure 1.1](#) illustrates the estimated post-harvest losses for key crops in Nigeria, according to the APHLIS database ([\(APHLIS\), 2019](#)).



**Figure 1.1:** PHL in Nigeria for key crops. Source: APHLIS database, 2019

Figure 1.2 shows post-harvest losses across different value chain steps from 2018 to 2022. The total estimated loss peaked in 2019 at over 2.2 million tonnes, followed by slight declines in subsequent years. The highest losses consistently occurred during the harvesting/field drying and household-level storage phases, which together accounted for over half of total losses in all years. Losses during further drying and threshing and shelling remained moderate but stable across the years. Transport from the field showed smaller but steady losses, while losses during transport to market and market storage were recorded as zero for all years, possibly due to either minimal losses or lack of data collection at those points. These trends suggest that targeted interventions in drying and storage practices could significantly reduce total post-harvest loss.



**Figure 1.2:** PHL loss in the various steps in the maize value chain. Source: APHLIS database, 2019

PHL is not just loss of food; it translates to loss in precious nutritional value. Maize for example is a staple food in Nigeria and PHL losses mean less nutrients for people. The data shows that, the amount of nutrients lost from PHL, equivalent to the average person's dietary requirements has been on the rise since the 2000s as Figure 1.3 shows.

### PHL equivalent % of people's annual dietary requirements (maize)

*PHL translates to real nutritional deficiencies...*



**Figure 1.3:** PHL expressed in the percentage of the average person's annual dietary requirements

Analysis of PHL loss in maize in 2022 is summarised in Table 1.1. For instance, the post-harvest loss of approximately 4.8 trillion kcal of energy and 878 million kg of carbohydrate alone could have met the annual energy and carbohydrate requirements of

over 5.7 million and 6.7 million people, respectively, across the total Nigerian population. These losses represent 2.9% and 3.5% of the total population's annual requirements for energy and carbohydrate. This is an obvious symptom of inefficiency in the food system that prevents available nutrients from reaching consumers.

The nutritional impact is particularly pronounced for vulnerable demographic groups, such as males aged 9-13 years. Within this focal group, the lost maize could have fulfilled the annual protein requirements for nearly 12.7 million individuals, a figure exceeding the total population of this demographic in 2022. This translates to a staggering 98.4% of the focal group's annual protein needs that were not met due to post-harvest losses.

**Table 1.1: Nutritional Impact of Maize Post-Harvest Losses in Nigeria, 2022**

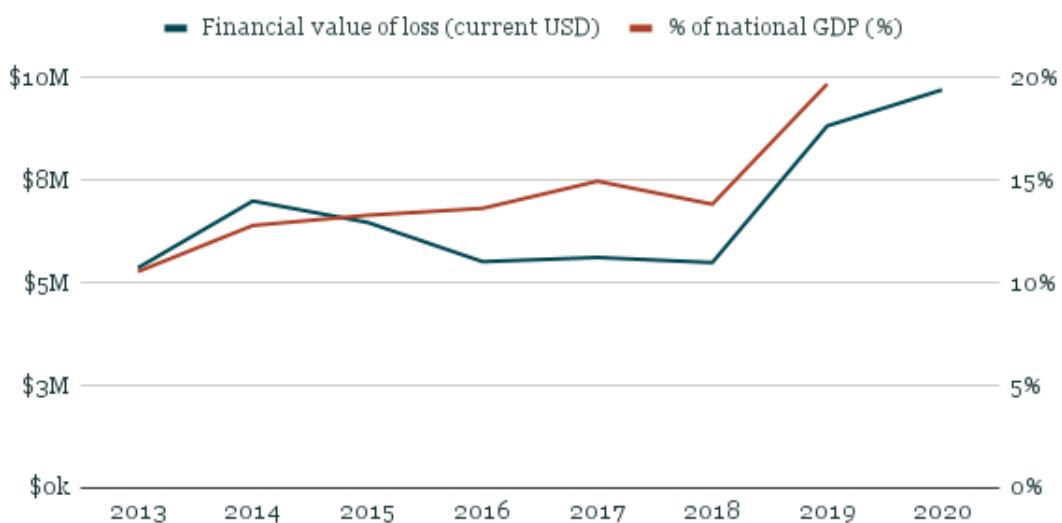
Nutrient	Quantity lost postharvest	Total population, Nigeria		Male, 9-13 years, Nigeria	
		Number of people's annual nutritional requirements lost	% of population nutritional requirements lost	Number of people in focal group's annual nutrient requirements lost	% of focal group population's annual nutritional requirements lost
Energy	4,797,678,189 kcal	5,771,644	2.9	5,752,439	44.7
Carbohydrate	878,428,757 kg	6,763,242	3.5	6,740,738	52.4
Protein	126,471,746 kg	10,744,369	5.5	12,664,398	98.4
Fat	56,362,409 kg	2,214,600	1.1	2,211,670	17.2
Fibre, total dietary	133,345,210 kg	11,522,627	5.9	11,420,111	88.8
Calcium, Ca	261,192 kg	864,988	0.442	650,540	5.1
Iron, Fe	42,615 kg	12,528,603	6.4	13,192,626	102.5
Zinc, Zn	21,308 kg	6,266,152	3.2	5,956,874	46.3
Folate, total	357.4 kg	3,686,759	1.9	3,916,933	30.4
Vitamin A (RAE)	0 kg	0	0	0	0
Vitamin C	0 kg	0	0	0	0

PHL also reflects as financial loss. Between 2013 and 2020, the financial impact of rice PHL grew from \$536,467,825 in 2013 to \$970,343,075 in 2020.

While the losses remained below 1% of the national agricultural GDP, the rising absolute value calls for attention to mitigation strategies to alleviate the effects on farmer's income, availability of rice to consumers and overall economic stability.

### Financial value of rice PHL (current USD), % of national GDP

Rice PHL amounts to almost 20% of national GDP in 2019



**Figure 1.4:** Financial value of rice PHL loss in Nigeria from 2013 to 2020. Source: APHLIS database, 2019

## 1.2 Impact on Youth and National Economy

PHL have far-reaching consequences for Nigeria's economy and youth engagement in agriculture. Economically, PHL represents wasted farmer income and lost food value, with maize losses alone accounting for approximately 0.9% of agricultural GDP. Furthermore, the inefficiency in food production results in under-utilized land—31% of Nigeria's cropland—and contributes to 5% of the country's greenhouse gas emissions. These losses inflate food prices, exacerbate food insecurity, and weaken national economic stability.

Beyond economic concerns, PHL directly affects Nigeria's youth, the largest segment of the population. The agricultural sector, despite its substantial contribution to the GDP (around 24%), is dealing with a dwindling workforce due to an aging farming population and the discouraging effects of post-harvest losses. Young people, who could drive innovation and modernization in agriculture, often view the sector as unappealing due to the visible waste and financial risks. Watching hard-earned produce deteriorate before reaching consumers discourages entrepreneurial efforts and limits agriculture's potential as a viable career path.

Reducing post-harvest losses is therefore crucial to stabilizing the economy and making agriculture more attractive to younger generations. It would increase food availability without requiring expansion of farmland, improve farmers' livelihoods, and foster a more resilient food system. Addressing PHL could encourage youth participation in agriculture, helping Nigeria move toward food self-sufficiency and boosting export potential. In essence, tackling post-harvest waste is not just about protecting farmers—

it's about securing Nigeria's future.*nd iv)* designing it to be user-friendly, especially for newcomers.

# 2

## Contributory factors to PHL in Nigeria

This chapter examines the primary factors driving Nigeria's post-harvest losses – poor transportation infrastructure, inadequate storage and cold-chain capacity, and limited market access – and explains how each contributes to the problem.

### 2.1 Poor Transportation Infrastructure

Nigeria's road and transport network is widely cited as a major culprit in post-harvest loss. Most rural roads are unpaved and poorly maintained, making travel slow, costly, and unreliable ([The Pinnacle Times, 2024](#); [Voice of Nigeria, 2023](#)). In fact, about 80% of Nigerian feeder roads are unpaved and become impassable during the rainy season ([The Pinnacle Times, 2024](#)). This forces farmers to make long, bumpy trips to market on motorcycle or in old trucks. One maize farmer in Osun State lamented that after harvesting, “we have no means of transporting [products] to urban centres...we eat what we can while a good percentage wastes away” ([The Pinnacle Times, 2024](#)).

Bad roads and inadequate vehicles increase both transit time and physical damage to produce. Perishable crops (tomatoes, peppers, leafy vegetables) begin to spoil or get bruised during long journeys in hot, open trucks. In one reported case, a Kano tomato farmer drove 14 hours in a non-air-conditioned van on a 32°C day; by the time his produce reached market, the tomatoes were already “rotting” and often thrown away unsold ([Ikegwuonu, 2018](#)). Such delays and heat stress can reduce shelf life from days to hours. Even for storable staples (maize, rice, yams), poor roads mean farmers often wait too long before selling; delays invite pests (weevils, rodents) and moisture damage during transport.

This infrastructure gap has been quantified in national studies. For example, the Food

and Agriculture Organization (FAO) estimates that up to 40% of Nigeria's agricultural output is lost post-harvest due to inadequate infrastructure ([The Pinnacle Times, 2024](#)). Government officials also emphasize that improving rural roads can directly cut losses: according to Nigeria's Rural Access Project coordinator, better feeder roads and bridge repairs would "reduce post-harvest losses, cost of transportation and accident rates" for farmers [citepVoiceofNigeria2023](#).

In short, the combination of long distances, rough roads and few refrigerated trucks means a large share of freshly-harvested crops never reach markets in good condition.

### 2.1.1 Key effects of poor transportation

**Delays and spoilage:** Long travel times on bad roads (often on footpaths or seasonal tracks) expose produce to heat, moisture and pests, so fruits and vegetables rot en route ([Ikegwuonu, 2018](#)).

**Physical damage** Bumpy rides in unpadded vehicles bruise grains and produce, leading to quality losses. Crushed bags attract pests and mold.

**High costs and leakage** Weak logistics force farmers to pay steep transport fees, effectively shrinking their margins. Some give up on distant markets altogether, dumping excess harvest near the farm.

Together, these factors mean that many Nigerian farmers see double-digit percentage losses just due to transit. For instance, data from the African Postharvest Losses Information System (APHLIS) shows 17% of Nigeria's maize is lost from harvest through delivery ([APHLIS](#)) ([2019](#))- and that figure would be higher on poor roads.

### 2.1.2 Inadequate Cold Storage and Processing

Another root cause of Nigeria's post-harvest losses is the near-absence of cold-chain and storage facilities. Most Nigerian farmers and traders have no access to refrigerated warehouses or cooling trucks. After harvest, highly perishable goods like tomatoes, fruits, vegetables, dairy and meat immediately begin to deteriorate without temperature control ([Organisation for Technology Advancement of Cold Chain in West Africa \(OTACCWA\), 2025](#)).

Nigeria's climate and power constraints make this especially severe. In most rural areas, electricity is intermittent or unavailable, and conventional refrigerators require too much power. As one report notes, "unlike the United States and Europe...cold refrigeration is virtually nonexistent in [Nigerian] farms and marketplaces" ([Ikegwuonu, 2018](#)).

The impact is dramatic: one analysis found that about 45% of Nigeria's perishable produce spoils at some point after harvest solely because of lack of cold storage ([Ikegwuonu, 2018](#)). Without refrigeration, simple transport times of a day or two can be fatal. For example, in the IFPRI ColdHubs case study above, tomatoes lost roughly two-thirds

of their market value by afternoon due to heat and rot ([Ikegwuonu, 2018](#)). Similarly, fruits like mangoes or watermelons will ferment or shrivel if not cooled within hours. Even root crops (cassava, yams) and grains lose quality if stored too long without drying or cooling; high humidity in sacks leads to mold and aflatoxins.

Moreover, Nigeria lacks processing and value-addition facilities that could reduce spoilage. For instance, small-scale drying kilns, canning plants, or flour mills are rare in many regions. If farmers had accessible rice mills or tomato canneries nearby, they could convert part of their harvest to shelf-stable products, greatly extending shelf life. In reality, most produce must be sold raw. This mismatch means that whenever markets glutted after harvest, farmers often have no choice but to sell quickly at low prices or waste the excess.

In sum, the lack of a modern cold chain (from farm to market) means Nigeria forfeits nearly half its high-value harvest to heat and spoilage ([Ikegwuonu, 2018](#); [Organisation for Technology Advancement of Cold Chain in West Africa \(OTACCWA\), 2025](#)). Experts note that “a modern cold chain system, combined with improved infrastructure and logistics, will be key to mitigating these losses” ([Ikegwuonu, 2018](#); [Organisation for Technology Advancement of Cold Chain in West Africa \(OTACCWA\), 2025](#)). As it stands, perishables often never reach peak freshness, and farmers’ incomes suffer accordingly.

### 2.1.3 Limited Market Access and Information

A related factor is how market barriers amplify post-harvest losses. Many smallholder farmers in Nigeria are geographically or socially isolated from buyers. Poor linkages mean harvests cannot be sold quickly and efficiently. Key issues include:

**Fragmented production:** Nigerian farms are small and scattered. Most farmers sell independently in local village markets. Without aggregation, they face high transaction costs transporting small loads, and cannot negotiate strong prices. The [Farm Support Solutions \(FSSS\) \(2025\)](#) notes that fragmented production and inconsistent quality “reduces market acceptance” and makes rural supply chains inefficient. When multiple small producers simultaneously bring the same crop to town, local prices crash and some output cannot be sold at all.

**Lack of price and demand information:** Many farmers do not have real-time data on market prices or demand trends. Without mobile market services or cooperatives, they often sell based on gut feeling. This information gap means farmers miss opportunities to time their sales for higher prices or send produce where demand is growing. In practice, it leads to gluts in some markets (driving prices down and unsold stacks to waste) while other regions suffer shortages. As FSSS reports, “limited market information...leads to low economies of scale” and exacerbates waste ([Farm Support Solutions \(FSSS\), 2025](#)).

**Inefficient value chains:** Poor market access also results from missing infrastructure

and services. For example, contract storage (warehouse receipt systems) or cold trucks for linking farmers to distant processors are largely unavailable. Without these, farmers often face long waits or forced distress sales. Research in Nigeria has noted that inadequate marketing systems and governance gaps in distribution (such as lack of financing for storage) are key socio-economic causes of loss ([Ogundele, 2022](#)).

In other words, even if crops survive transport, market inefficiencies can leave them unsold. For instance, one survey found that almost half of smallholder farmers were unable to sell their preferred quantity because of volatile prices and a lack of buyers

Addressing market access could dramatically cut losses: digital marketplaces and aggregation hubs are emerging as solutions. By connecting farmers directly with buyers and sharing price information, such platforms reduce the risk of unsold crop. For example, pilot programs like Foodstuff Store and Soluta leverage mobile apps to link remote farmers with city consumers and traders, helping ensure produce finds a market quickly ([Tenebe, 2024](#); [Farm Support Solutions \(FSSS\), 2025](#)). These innovations hint at how improved market linkages can complement transport and storage solutions.

#### 2.1.4 Conclusion

Nigeria's high post-harvest losses have clear, practical causes rooted in infrastructure and market systems. In summary: crumbling rural roads and transport mean crops spoil before sale ([The Pinnacle Times, 2024](#); [Voice of Nigeria, 2023](#)) ; absence of cold storage and processing leaves perishables to rot or shrivel ([Ikegwuonu, 2018](#); [Organisation for Technology Advancement of Cold Chain in West Africa \(OTACCWA\), 2025](#)) ; and poor market integration forces farmers into inefficient, wasteful sales patterns ([Farm Support Solutions \(FSSS\), 2025](#)). These problems are interlinked: for example, even if transport is available, the benefit is lost if there is nowhere to store or sell the produce at proper prices. Studies emphasize that tackling Nigeria's PHL requires a multifaceted approach. The challenges are "complex and interrelated," so solutions must combine technical fixes with economic and policy reforms ([Ikegwuonu, 2018](#); [Abulude et al., 2024](#)).

In practice, this means investing in all links of the chain: paving and maintaining feeder roads and bridges, expanding clean energy for cold storage, supporting local processing centers, and empowering farmers with market data and aggregation mechanisms. According to experts, "a modern cold chain system, combined with improved infrastructure and logistics, will be key to mitigating these losses" ([Ikegwuonu, 2018](#)).

In conclusion, reducing Nigeria's PHL burden (currently on the order of tens of billions of naira per year) hinges on strengthening the transportation-storage-market triad. Hackathon innovations that create digital marketplaces or logistics solutions directly address this nexus. By helping farmers find buyers and manage their produce more efficiently, such tools can cut waste and preserve value. In doing so, they support food

security and farmers' incomes – goals that depend squarely on fixing the infrastructure and informational gaps highlighted above.

# 3

## Okra: Our Solution Proposal

### 3.1 Core Concept and Functionality

Okra is a mobile-first, web-enabled platform designed as a comprehensive ecosystem to mitigate PHL. (View Okra here <https://okra-ai.vercel.app/>) The platform serves three primary user groups:

**Farmers/Producers:** Can create profiles, list their produce (crop type, quantity, harvest date, location), upload images for AI assessment, set indicative prices, and view market demand.

**Buyers** Can search for specific produce based on type, quantity, quality (informed by AI score), and location. They can connect with farmers, negotiate, and arrange purchases. Buyers include wholesalers, retailers, processors, and direct consumers.

**Logistics Providers** Can register their services (vehicle type – including refrigerated options, capacity, operational routes, pricing). The platform facilitates matching them with farmers/buyers needing transport.

#### 3.1.1 Marketplace Networking

Farmers and producer groups register on the app to list available produce (crop type, quantity, harvest date). Buyers – including wholesalers, processors, and retailers – can search and place orders by region and crop. By centralizing listings, the app ensures farmers find customers quickly, and buyers can discover sources of fresh produce. This reduces unsold inventory and match supply to demand in real time.

#### 3.1.2 Logistics Integration

The app includes a dashboard for logistics providers (truckers, couriers, cold-chain operators). When a sale is made, the system can automatically offer transport jobs to verified drivers. Users can see available vehicles, rates, and track shipments. For

example, a farmer in Kano could schedule a refrigerated truck to deliver tomatoes to Lagos. This ensures reliable transport capacity and route planning, cutting delays that lead to spoilage.

### 3.1.3 AI-Powered Insights

A novel AI feature uses computer vision to analyze produce quality. Farmers or cooperatives upload smartphone images of their harvest batches. The app's AI model assesses freshness (e.g. spotting bruises, mold, color) and estimates volume or weight from the images. This accomplishes two goals: (1) It provides an objective quality grade for buyers to see, increasing trust. (2) It forecasts how long the produce will remain saleable. The model improves over time as more labeled images are fed back, refining its predictions.

### 3.1.4 Youth-led Agribusiness Empowerment

The platform encourages youth entrepreneurship. For example, tech-skilled youth can be trained to help digitize farms (taking images, using the app), to become last-mile delivery drivers, or to manage aggregation hubs. The platform could partner with agricultural colleges or startup incubators to recruit graduates. By framing agriculture as a tech-enabled business, the app draws young people into value chains. In effect, it transforms farming from subsistence into a connected, data-driven marketplace, which is more attractive to the next generation.

---

#### Note

*Because of the time span of the hackathon, development of the Okra web app is not complete. Part of the frontend and most of the backend are still in development. The following sections show the current state of the project, including the mockups and the data strategy.*

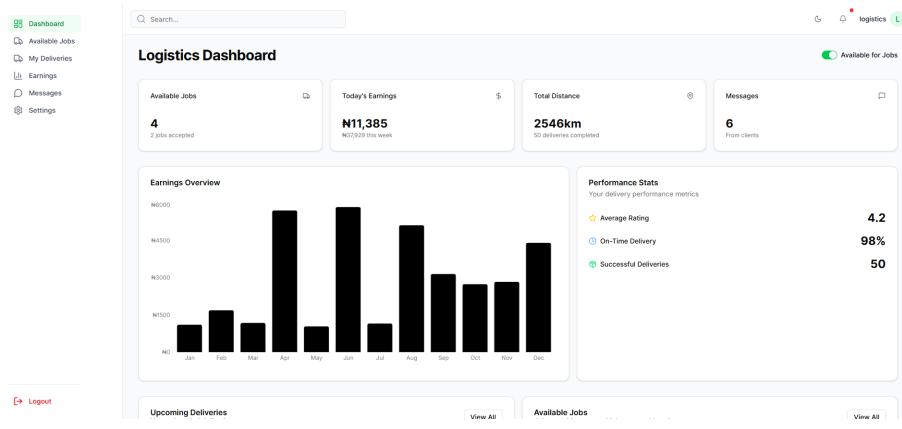
## 3.2 Screens



Figure 3.1: Screenshot of the landing page

Figure 3.2: Screenshot of the farmer's dashboard

Figure 3.3: Screenshot of the buyer's dashboard



**Figure 3.4:** Screenshot of the buyers's dashboard

## 3.3 Data Strategy

### 3.3.1 Image Data Collection

We will collect large numbers of labeled images of harvested produce. This will be done in phases: initially, a pilot program in a few regions (e.g. Kano for tomatoes, Adamawa for maize) will train extension agents and youth volunteers to photograph produce at harvest and at sale. Each image will be tagged with metadata (crop type, variety, region, time, moisture, storage conditions, etc.). Over time, farmers using the app will also upload photos for every batch they list, creating a growing dataset.

### 3.3.2 Data Labeling and Training

Using expert agronomists and community training, images will be labeled for freshness (e.g. "Fresh", "Moderately aged", "Spoiled") and total count/weight. This labelled dataset feeds the computer vision model. We will employ transfer learning on convolutional neural networks so the AI can accurately assess new images it has not seen before. The initial model will be tested for accuracy and iteratively improved as more data arrives.

### 3.3.3 Feedback Loop (Active Learning)

Post-deployment, the app will track outcomes of predicted vs. actual. For example, if the AI predicts 10 days of shelf life but spoilage occurs in 7 days, this discrepancy is logged. Buyers and farmers can rate or report the accuracy of freshness ratings. This feedback is used to retrain the model periodically, increasing its accuracy over time. In effect, the app learns from real-world results.

## 3.4 Auxiliary data sources

In addition to user-generated data, the system will integrate public and commercial datasets for context. Possible sources include:

**Crop statistics:** Government or FAO data on regional production volumes and seasonality for major crops.

**Geolocation** Maps of farm locations, major roads, market centers.

**Weather/Climate** Historical and current weather data per region, since humidity and temperature affect spoilage.

**Market Prices** Data from local commodity exchanges or market surveys, to show price trends.

**Demographic Data** Farm population and sizes, to profile areas served. This external data enriches the dashboard: for instance, linking rainfall patterns to losses in maize, or highlighting regions that produce a given crop. All data is tied to time and location, enabling spatio-temporal analysis.

### 3.4.1 Privacy and Governance

Farmers' personal data (names, exact addresses) will be protected. Only aggregate or anonymized data used on dashboards. Data use agreements will ensure that insights (e.g. "X tonnes of tomatoes sold from Kano") respect user privacy while guiding decisions.

## 3.5 OkraAI

Okra features a Fruit Ripeness Prediction tool, using computer vision (CV), a specialized branch of machine learning that enables computers to analyze and interpret visual data from images. This technology facilitates the detection and prediction of fruit and vegetable freshness.

For this object detection task, the YOLOv11 model was specifically chosen due to its:

**Speed:** YOLOv11 is known for its fast processing speed, making it suitable for real-time applications.

**Accuracy:** It achieves high accuracy in detecting and classifying objects within images.

**Flexibility:** The model can be trained on various datasets, allowing it to adapt to different types of produce.

### 3.5.1 Dataset

A hybrid dataset was constructed by combining multiple primary and secondary datasets. This approach aimed to enhance the model's generalization capabilities and ensure a broad representation of fruit ripeness stages. The dataset includes the following classes:

- Ripe
- Unripe
- Rotten

Data sources include:

1. **Ripe Orange Dataset:** Primary data collected and annotated by Team Okra.
2. **Tomato Checker Dataset:** Source: Roboflow (<https://universe.roboflow.com/money-detection-xez0r/tomato-checker/dataset/>).
3. **Banana Ripeness Dataset:** Source: Roboflow (<https://universe.roboflow.com/arm-oeppz/banana-8qkur/dataset/2>).
4. **Rot Detection:** Source: Roboflow ([https://universe.roboflow.com/srmist-doq3j/rot\\_detection/dataset/13](https://universe.roboflow.com/srmist-doq3j/rot_detection/dataset/13)).
5. **Orange Dataset 2:** Source: Roboflow ([https://universe.roboflow.com/mert6107/orange\\_detection-5f84p/dataset/](https://universe.roboflow.com/mert6107/orange_detection-5f84p/dataset/)).

This dataset includes prevalent perishable fruits and vegetables including bananas, oranges, eggplants, garden egg, spinach, grapes, tomatoes, and cucumbers.

## 3.6 Data Split

The combined dataset was divided into training and validation sets using a 70:30 split.

**Table 3.1:** Class distribution before re-splitting

No. of Images	Ripe	Rotten	Unripe
Train	3000	2879	2105
Train Split	2100	2015	1473
Validation Split	900	864	632

## 3.7 Model Training

The pretrained YOLOv11s model was fine-tuned using the custom dataset, running with Pytorch and Ultralytics within the free tier Google Colaboratory environment. The compute environment specifications were: 112GB ROM, 12.7GB RAM, and a T4 GPU with 15GB RAM. The hyperparameters were set as follows:

**Model:** yolov11s (selected for a balance between speed and accuracy)

**Epochs:** 20

**Image Size:** 640

**Optimizer:** AdamW (learning rate = 0.001429, momentum = 0.9)

The training process was completed in 0.797 hours. The model's performance on the validation set is summarized in the table below:

## 3.8 Deployment

The YOLOv11s model achieves a mean Average Precision (mAP50) of 0.847 and an mAP50-95 of 0.65, excelling at fruit discrimination with high precision (Box(P)) and

**Table 3.2:** Model performance on the validation set.

Class	Images	Instances	Box(P)	Box(R)	mAP50-95
all	2396	3938	0.822	0.802	0.65
ripe	900	1077	0.896	0.949	0.895
rotten	864	1810	0.703	0.530	0.332
unripe	632	1051	0.868	0.928	0.721

*Speed:* 0.2ms preprocess, 5.1ms inference, 0.0ms loss, 2.0ms postprocess per image.

recall (Box(R)) scores, and consequently, high mAP50 and mAP50-95 values. This indicates that the model is both accurate in its detections and effectively identifies most instances of these classes.

However, the model shows a comparatively lower performance in detecting rotten fruits. The precision (0.703) and recall (0.53) are notably lower than those for ripe and unripe categories, resulting in a lower mAP50 (0.62) and a significantly lower mAP50-95 (0.332). This suggests that the model may be less accurate in identifying rotten fruits and might miss a significant portion of them.

The inference speed of 5.1ms per image, after preprocessing and postprocessing, indicates that the model is efficient for real-time applications.

### 3.9 Confusion Matrix

The confusion matrix shows that the YOLOv11s model effectively classifies ripe (1015), rotten (1034), and unripe (984) fruits, reasonably well. However, there were significant misclassifications of background as rotten (766), and some ripe (119) and unripe (147) fruits were confused with background. Despite these errors, misclassifications between ripeness categories were low, showing reliable differentiation between maturity stages. While performing well, the model's robustness could be improved by more background data and stronger regularization to reduce false positives.

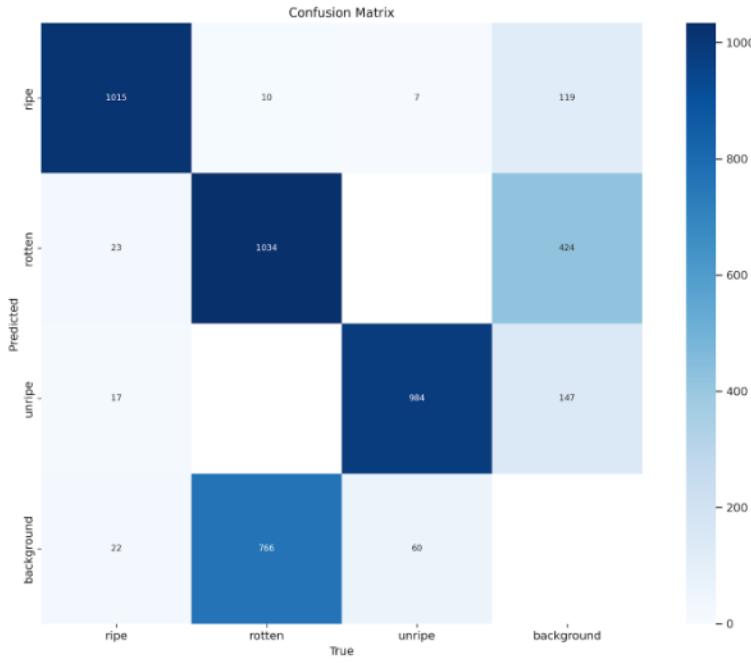


Figure 3.5: Confusion matrix of the model

## 3.10 Training Progression

The metric progression shows a consistent trend of improvement with increasing epochs, indicating effective learning and minimal overfitting. The proximate training and validation scores further underscore the model's generalizability to unseen images. Visual analysis reveals that at epoch 20, the terminal iteration, the model attains optimal performance, displaying the nadir of loss values and the apex of mean Average Precision (mAP), Precision, and Recall scores.

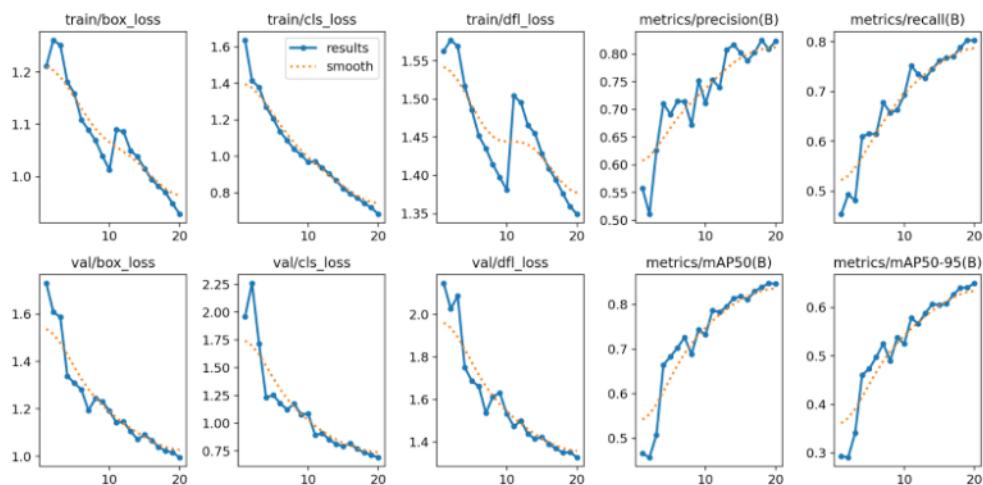
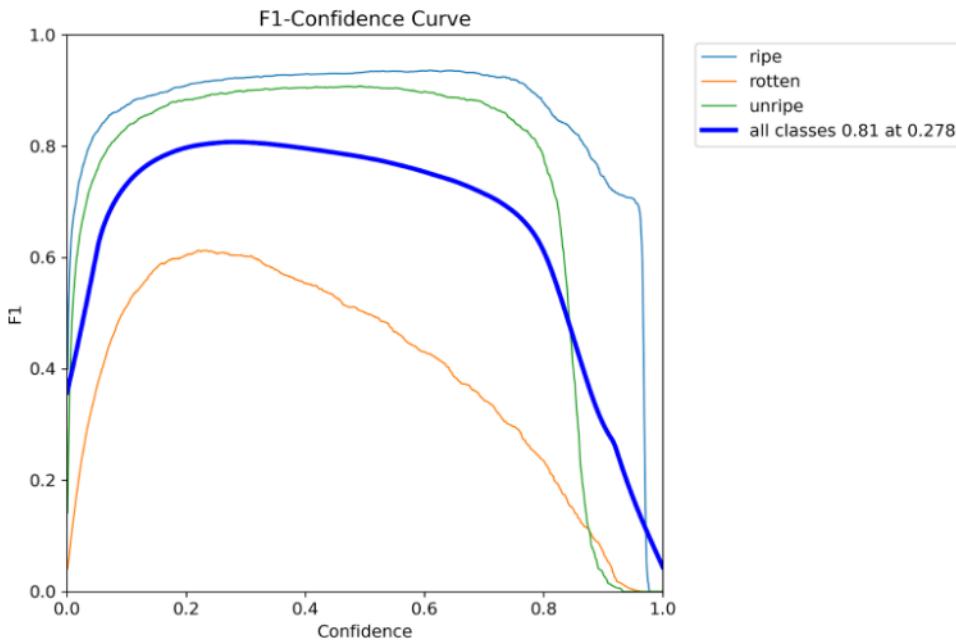


Figure 3.6: Training progression of the model

### 3.11 F1-Confidence Curve

The F1-confidence curve in [Figure 3.7](#) illustrates the F1-score across various confidence thresholds. A higher F1-score indicates a more effective model in differentiating between the dataset's classes. Our model achieves a peak F1-score of 0.81 (81%) at a confidence threshold of 0.278. This suggests that for optimal deployment, the recommended confidence threshold should be approximately 0.3.

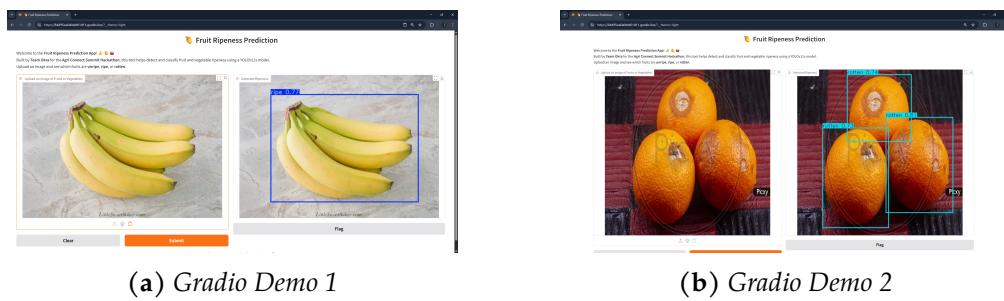


**Figure 3.7:** F1-confidence curve of the model

### 3.12 Deployment and Demo

For integration into the Okra app, the trained YOLOv11s model was exported to the ONNX (Open Neural Network Exchange) format ([ONNX Community, 2019](#)). ONNX is a widely supported format for representing neural network architectures, facilitating deployment across diverse platforms such as mobile devices, web applications, microcontrollers, and servers.

To showcase the model's capabilities, a demonstration web application was developed using the Gradio tool. Images illustrating the model in operation are provided below.



**Figure 3.8:** Gradio Demo of the model



# Bibliography

(APHLIS), African Postharvest Losses Information System (2019). *APHLIS Database: Postharvest loss estimates for Sub-Saharan Africa*. Accessed: 6 May 2025. URL: <https://www.aphlis.net>.

Abulude, Ifeoluwa and Stefan Wahlen (2024). *Food Loss Analysis in Nigeria: A Systematic Literature Review*. Available at SSRN. URL: <https://ssrn.com/abstract=4920743>.

FAO (n.d.). *Post-Harvest System and Food Losses*. Accessed: 7 May 2025. URL: <https://www.fao.org/4/AC301E/AC301e03.htm>.

Farm Support Solutions (FSSS) (Feb. 13, 2025). *Unlocking Market Access through Aggregation for Smallholders in Nigeria: 2024 Annual Impact Report*. URL: <https://fssolutions.org/market-access/2024-report-unlocking-market-access-through-aggregation-for-smallholders-in-nigeria> (visited on 05/10/2025).

Ikegwuonu, Nnaemeka C. (Nov. 20, 2018). *ColdHubs: Addressing the crucial problem of food loss in Nigeria with solar-powered refrigeration*. IFPRI blog. URL: <https://www.ifpri.org/blog/coldhubs-addressing-crucial-problem-food-loss-nigeria-solar-powered-refrigeration> (visited on 05/10/2025).

Nigeria, News Agency of (2024). “Nigeria loses 50% of agricultural produce post-harvest—FAO”. In: *Premium Times*. Accessed: 6 May 2025. URL: <https://www.premiumtimesng.com/agriculture/agric-news/739762-nigeria-loses-50-of-agricultural-produce-post-harvest-fao.html>.

Ogundele, Femi (2022). “Post Harvest Losses and Food Security in Nigeria: An Empirical Review”. In: *African Journal of Agriculture and Food Science* 5.3, pp. 77–89. doi: [10.52589/AJAFSC0442Z7J](https://doi.org/10.52589/AJAFSC0442Z7J).

Okojie, J. and F. Jaiyesimi (2024). *Annual N3.5trn post-harvest loss swallows five-year agric budget*. Businessday NG. Accessed: 6 May 2025. URL: <https://businessday.ng/agriculture/article/annual-n3-5trn-post-harvest-loss-swallows-five-year-agric-budget/>.

ONNX Community (2019). *Open Neural Network Exchange (ONNX)*. <https://onnx.ai/>. Accessed: 2025-05-15.

Organisation for Technology Advancement of Cold Chain in West Africa (OTACCWA) (Feb. 19, 2025). *Tackling Nigeria's N3.5 trillion post-harvest losses.* URL: <https://thenationonlineng.net/tackling-nigerias-n3-5-trillion-post-harvest-losses> (visited on 05/10/2025).

Tenebe, Diana (May 2024). "Smallholder farmers need digital marketplaces to curb post-harvest losses- Diana Tenebe, COO, Foodstuff Store". In: *Businessamlive*. URL: <https://www.businessamlive.com/smallholder-farmers-need-digital-marketplaces-to-curb-post-harvest-losses-diana-tenebe-coo-foodstuff-store/>.

The Pinnacle Times (June 25, 2024). *Boosting Food Production in Nigeria through Improved Rural Feeder Roads.* Column. URL: <https://thepinnacletimes.com.ng/boosting-food-production-in-nigeria-through-improved-rural-feeder-roads/> (visited on 05/10/2025).

Udi, A. (2024). *Post-harvest losses for fresh produce at almost 50% in Nigeria – USAID.* Nairametrics. Accessed: 6 May 2025. URL: <https://nairametrics.com/2024/04/21/post-harvest-losses-for-fresh-produce-at-almost-50-in-nigeria-usaid/>.

Voice of Nigeria (Sept. 15, 2023). *Rural access roads will reduce post-harvest losses – coordinator.* URL: <https://von.gov.ng/rural-access-roads-will-reduce-post-harvest-losses-coordinator> (visited on 05/10/2025).

World Bank (2020). *Nigeria Food Smart Country Diagnostic.* Washington, DC: World Bank.



