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Option : Artificial Intelligence

SYMBIOSE: Creation of a prototype smart bin enabling data collection (laboratory bin)

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Dedication

To my mother, who taught me that nothing is impossible for a woman, and to every woman in my family whose success showed me, before I ever needed to be told, that my only limits were the ones I accepted.

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To my friends and cousins: Thank you for your unconditional support (and your garbage).

"When the last tree has been cut down, the last fish caught, and the last river poisoned, only then will we realize that one cannot eat money."

-Native American Proverbe

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List of Acronyms

Acronym	Meaning
ADDA	Adversarial Discriminative Domain Adaptation
AI	Artificial Intelligence
APC	Assemblée Populaire Communale (People's Municipal Assembly)
B2B	Business-to-Business
B2G	Business-to-Government
BiFPN	Bidirectional Feature Pyramid Network
CBAM	Convolutional Block Attention Module
CNN	Convolutional Neural Network
CvT	Convolutional Vision Transformer
DANN	Domain-Adversarial Neural Network
DZD	Algerian Dinar
EPR	Extended Producer Responsibility
ESG	Environmental, Social, and Governance
EU	European Union
FP16 / FP32	16-bit / 32-bit Floating Point (precision)

FPN	Feature Pyramid Network
GAN	Generative Adversarial Network
GDP	Gross Domestic Product
GPI	Genuine Progress Indicator
GPS	Global Positioning System
GPU	Graphics Processing Unit
HOG	Histogram of Oriented Gradients
INT8	8-bit Integer (quantization precision)
IoU	Intersection over Union
KNN	K-Nearest Neighbors
LBP	Local Binary Patterns
LSTM	Long Short-Term Memory
mAP	mean Average Precision
MENA	Middle East and North Africa
NAS	Neural Architecture Search
NIMBY	Not In My Backyard
NIR	Near-Infrared (spectroscopy)
ONNX	Open Neural Network Exchange
PET	Polyethylene Terephthalate
QAT	Quantization-Aware Training
ReLU	Rectified Linear Unit
ResNet	Residual Network
RGB	Red, Green, Blue (color image channels)
SaaS	Software as a Service
SE	Squeeze-and-Excitation (block)
SSD	Single Shot MultiBox Detector
SVM	Support Vector Machine
TACO	Trash Annotations in Context (dataset)
TPU	Tensor Processing Unit
TTA	Test-Time Augmentation
UDA	Unsupervised Domain Adaptation

UI/UX	User Interface / User Experience
VGG	Visual Geometry Group (network)
ViT	Vision Transformer
VOC	Visual Object Classes (Pascal VOC annotation format)
XML	Extensible Markup Language
YOLO	You Only Look Once (object detection architecture)

Introduction.

Contexte:

We've broken the symbiosis between humans and nature. We generate waste we can't manage.
Algeria is running out of landfill space. Within a few years, the country will lack sufficient land to bury its waste triggering cascading consequences across public health, the economy, tourism, and international penalties against Algeria [4].
Trash pollutes landfills, the sea, fuels wildfires, releases toxic gases, and accelerates climate change. There's no circularity or respect to nature in how we discard. This outdated system harms the country and the citizens and reveals a deeper crisis in how we live, consume, and coexist with nature.
In Tlemcen, this crisis manifests daily as unsorted household waste polluting streets, a visible symptom of a waste management system that is outdated. This crisis incurs substantial economic costs and negatively impacts multiple sectors.
Globally, artificial intelligence is increasingly integrated into waste management systems. Singapore serves as a notable example, heavily incorporating AI into waste management to address land constraints and enhance recycling rates [5]. Technologies include AI-powered smart bins, robotic sorting at material recovery facilities, and sensor-driven collection logistics aimed at achieving a zero-waste circular economy. Singapore employs a hybrid architecture combining computer vision with physical sensor data to address the complexity of mixed garbage. This demonstrates that AI can function effectively in real-world waste conditions, Algeria could adapt similar approaches with locally representative data. If we can modernize how we handle waste, we create more than just a cleaner city, we create green jobs, better public health, and a tangible way for our community to actively contribute to a future they can be proud of.

Problem Description

The primary problem addressed in this thesis is the absence of accessible and realistic datasets on Algerian waste, specifically on Tlemcenian waste. No dataset accurately reflecting local conditions is currently available. One dataset was developed in Tiaret, but it is not accessible for further research and the type of data collected to train the model are for the third level of the waste management cycle life which is the recycling facility level, but most waste, when already contaminated at source, is hard to recycle or repurpose later on and it valorisation is lower [6]. Sorting at source is the primary challenge residents do not exert effort in waste separation, lack awareness [2], and past awareness campaigns by local authorities achieved limited results.This data gap also constitutes the fundamental bottleneck preventing AI-based waste management solutions from being deployed in Algeria.

The core problem is therefore twofold:
(1) no accessible realistic dataset exists on Algerian household waste
(2) sorting at source remains unresolved due to low public awareness and lack of incentives.
This project is essential as it establishes the foundational infrastructure for any technology-oriented solution in Tlemcen, enabling AI-based sorting, waste valorization, and

reduction of environmental consequences when waste is not sorted and recycled adequately. Without locally representative data, AI systems cannot be trained to recognize Algerian waste characteristics, packaging, and composition at source.

Contribution

This thesis focused on household waste as the entry point, open source datasets and pre-trained models were examined from Kaggle, all trained on Western data. Images were tested on a specific dataset selected for its focus on household waste. Results confirmed that Western-trained models perform poorly on local waste due to significant differences in composition, packaging, and appearance. This empirically demonstrates the critical need for a locally representative dataset and adapted AI models.

This thesis delivers three concrete contributions:

1. An entry point for a realistic dataset on Tlemcenian household waste, addressing the critical data gap that prevents AI deployment in waste management in the city.
2. A pre-trained YOLOv11 model from kaggle fine-tuned on the locally created and augmented dataset.
3. A theoretical study on the ideal smartbin to be deployed in Tlemcen to solve the waste problem at source, minimizing the impact of user mistakes and creating better quality waste with higher valorization while lowering contamination, and providing a good user experience.

This work establishes the entry point to AI-based sorting at source in Tlemcen, enabling authorities and citizens to sort waste effectively, increase recycling rates, extract value from waste, and reduce environmental harm. The project also supports the policy recommendation of reinforcing regulatory frameworks alongside customizable smart bin deployment.

Chapter 1:

The Waste Problem.

1.1 Introduction

Waste constitutes any material, substance, or by-product that is discarded, no longer desired, or lacks immediate utility or economic value. This encompasses items generated through human activities, industrial operations, or natural processes that are designated for disposal, recycling, or recovery. The conceptualization of waste has evolved significantly within contemporary environmental scholarship, moving beyond a simplistic notion of "discarded matter" to encompass broader considerations of resource management across an item's entire lifecycle.[7]

Household waste (also termed "domestic waste" or "municipal solid waste from households") refers to waste generated from residential activities within homes and dwellings. This includes ordinary refuse such as food scraps, packaging materials, paper, plastics, glass, metals, textiles, and garden waste that are typically collected through municipal waste management services. Household waste generally excludes hazardous materials, industrial waste, and construction debris, though it may occasionally contain small quantities of household hazardous waste (e.g., batteries, cleaning chemicals, paint). [8]

1.2. Treatment Methods for Waste Management: Functions and Potential Applications in the Algerian Context

Treatment Method	Functional Mechanism	Potential Role in Algeria
Recycling	Processes recyclable materials (plastic, paper, glass, metal) through mechanical or chemical treatment to produce new manufactured goods	Could recover 27–30% of household waste volume if properly implemented with source separation protocols
Composting	Facilitates aerobic decomposition of organic waste under controlled conditions to produce nutrient-rich soil amendment (compost)	Particularly suitable for Algeria given that 53.61% of municipal waste consists of organic/food waste fractions
Anaerobic Digestion	Decomposes organic waste in oxygen-free environments, generating biogas (renewable energy) and digestate (fertilizer by-product)	Offers dual benefits for Algeria: energy generation alongside waste reduction, addressing the high organic fraction of municipal waste

Incineration	Thermally oxidizes waste at elevated temperatures, with potential energy recovery through steam generation	Currently employed in Algeria; however, significant environmental drawbacks include air pollution emissions and destruction of recyclable material streams
Landfilling	Disposes of residual unsorted waste through burial in engineered containment sites	Represents the dominant waste management method in Algeria; however, environmental consequences include methane emissions and soil/water contamination risks

Table 1: Waste treatment methods and their relevance in Algeria

A. Contemporary situation in Algeria

Percentage of waste by material in Algeria:

Material	**Percentage**
Organic	53.61\%
Plastic	15.31\%
Disposable diapers	11.76\%
Paper	6.76\%
Textiles	4.5\%
Metals	1.72\%
Hazardous waste	1.07\%

Glass	1.04\%
Others	4.23\%
Total	**100\%**

B.E.T - E^3 "Environment – Ecology – Ecosystems" Tlemcen, "*Report AND 2020*"

Table 2: Waste composition by material in Algeria

1.3. Current Waste Treatment Methods in Algeria and Their Environmental and Economic Impacts

Algeria's current waste management infrastructure is predicated upon two environmentally unsustainable treatment methodologies: landfilling and incineration. These approaches fail to align with circular economy principles and generate significant negative environmental, economic, and public health consequences.

1.3.1 Landfilling: The Predominant Disposal Method

Operational Mechanism: Unsorted municipal waste is deposited and buried in open or semi-controlled landfill sites without prior separation or treatment.

Environmental Consequences:

1. **Methane Emissions:** Organic waste fractions undergo anaerobic decomposition within landfill matrices, releasing methane (CH_4), a greenhouse gas approximately 25 times more potent than carbon dioxide (CO_2) in terms of global warming potential.
2. **Soil and Groundwater Contamination:** Leachate generated from decomposing waste materials infiltrates surrounding soil matrices and contaminates aquifer systems, posing risks to freshwater resources.
3. **Land Resource Consumption:** Landfill facilities occupy substantial land areas, creating spatial conflicts particularly proximate to major urban centers including Oran, Algiers, and Annaba.
4. **Resource Finite Nature:** Landfill capacity is inherently limited. At current disposal rates, Algeria is projected to exhaust suitable landfill sites within 15–20 years, necessitating urgent alternative waste management strategies.

1.3.2. Incineration: Thermal Waste Treatment

Operational Mechanism: Municipal waste undergoes thermal oxidation at elevated temperatures, with occasional energy recovery through electricity generation.

Environmental Consequences:

1. **Air Pollution:** Incineration processes emit hazardous pollutants including dioxins, furans, and heavy metals (e.g., lead, mercury) derived from the combustion of plastic materials.
2. **Destruction of Recyclable Materials:** Plastic, paper, and metal fractions that possess recoverable value are destroyed rather than diverted to recycling streams.
3. **Toxic Ash Residues:** Both bottom ash and fly ash residues contain concentrated toxic compounds requiring specialized hazardous waste disposal protocols.
4. **Perpetuation of Waste Generation:** Incineration infrastructure incentivizes continued waste production rather than promoting waste reduction and source separation initiatives.

1.4. Systemic Failures of Current Algerian Waste Management

The inadequacy of Algeria's prevailing waste management approach stems from multiple interconnected deficiencies:

Deficiency	**Description**
Absence of Waste Sorting	Approximately 50% organic waste and 45% recyclable materials are co-disposed to landfills or incineration facilities without separation
Lost Economic Value	Recyclable materials buried in landfills represent forfeited revenue streams for the recycling industry
Environmental Degradation	Pollution from current methods negatively impacts public health in urban areas
Non-Circular Model	Algeria operates within a linear "take-make-dispose" framework rather than implementing circular economy principles

Table 3: Systemic failures in current Algerian waste management

The Recycling Disparity: Algeria Relative to International Standards

Comparative Recycling Rate Analysis

Region/Country	**Recycling Rate**
Algeria	5–7% of household waste
Developing countries (International norm)	~30%
European Union average	~48–52%
Germany (leading performer)	~67%

World Bank

Table 4: Recycling rate comparison

Algeria's recycling rate is approximately 4–6 times lower than the international benchmark for developing nations, indicating a substantial gap in waste management infrastructure and policy implementation.

Economic Implications of the Recycling Gap

Quantified Economic Losses from Inadequate Recycling

Impact Category	**Description**
Lost Raw Materials	Approximately 45% of waste composition (plastic, paper, glass, metal) possesses potential to substitute virgin materials in manufacturing processes
Import Dependency	Algeria imports recycled plastic pellets and paper pulp that could be domestically produced from recovered waste materials

Employment Losses	The recycling industry generates 6–10 times more jobs per tonne of waste compared to landfilling; Algeria forfeits this economic opportunity
Energy Inefficiency	Recycling aluminum conserves 95% energy relative to virgin production; recycling plastic conserves approximately 70% energy

Table 5: Economic losses caused by low recycling rates

While exact quantification varies across studies, empirical research suggests Algeria incurs annual economic losses exceeding hundreds of millions of dollars in unrecovered recyclable materials. This substantial economic deficit underscores the urgent necessity for comprehensive waste management reform incorporating source separation, recycling infrastructure development, and circular economy integration.

1.5. The Circular Economy and Its Relevance to Algeria

Figure 1: Circular Economy diagram, raw materials, design, production, retail, consumption, reuse & repair, collection, recycling, residual waste.

Definition and Conceptual Framework :

The circular economy represents a transformative economic system designed to fundamentally restructure material flow and resource utilization. This paradigm is characterized by four core principles: [16] [15]

1. Material Retention: Maintaining materials in productive use for extended durations rather than discarding them after single-use applications
2. Value Maximization: Extracting maximum economic and functional value from materials during their use phase through mechanisms including recycling, composting, and reuse
3. Natural System Regeneration: Restoring and regenerating natural ecosystems, exemplified by compost returning nutrients to soil matrices
4. Waste Elimination: Designing products with inherent durability, reuse potential, and recyclability to preclude waste generation at the systemic level

Comparative Analysis: Linear versus Circular Economic Models

Dimension	**Linear Economy (Current Algerian Model)**	**Circular Economy (Target Framework)**
Material Flow	Take → Make → Dispose	Take → Make → Use → Recover → Remake
Recycling Rate	5–7% of household waste	30–50%+ (EU average)
Waste Conceptualization	Waste as trash destined for landfill	Waste as resource for new production
Material Sources	Virgin materials exclusively	Recycled materials combined with virgin materials
Environmental Outcome	Pollution and resource depletion	Regeneration and sustainability

Table 6: Linear and circular economic models in Algeria

Application of Circular Economy Principles to Algeria's Waste Composition

Empirical analysis of Algeria's household waste composition reveals substantial potential for circular economy implementation:

Waste Fraction	Percentage	Circular Economy Solution	Economic Value
Organic/Food Waste	53.61%	Composting → fertilizer for agriculture; Anaerobic digestion → biogas (energy) + digestate (fertilizer)	Algeria's agricultural sector could achieve millions in savings on imported fertilizers
Plastic (Packaging)	15.31% of total waste	Recycling → plastic pellets → new bottles, containers, pipes	Reduction in plastic imports; creation of recycling industry employment
Paper/Cardboard	6.76%	Recycling → paper pulp → new packaging, newspapers	Development of local paper production capacity versus import dependency
Glass	1.04%	Recycling → glass granules → new bottles, jars	Infinite recyclability without quality degradation
Metals	1.72%	Recycling → aluminum/steel → new cans, parts	Aluminum recycling conserves 95% energy relative to virgin production

Table 7: Circular economy applications for Algeria's waste composition

Quantified Circular Economy Potential

If Algeria implements comprehensive sorting and recovery systems for these waste fractions, the following outcomes are achievable:

- Material Recovery: 45–50% of waste transitions from disposal to resource utilization.

- Landfill Extension: Landfill volume reduction by approximately 50%, extending landfill lifespan by 10+ years.
- Industrial Development: Establishment of composting facilities, recycling plants, and biogas production infrastructure.
- Employment Generation: The recycling sector generates 6–10 times more jobs per tonne compared to landfilling operations.

Structural Barriers Preventing Circular Economy Implementation in Algeria

Barrier	Current Situation	Required Interventions
Absence of Source Sorting	All waste streams are mixed and directed to landfill or incineration.	Implementation of separate collection bins and smart sorting technologies.
Inadequate Recycling Infrastructure	Recycling rate of 5–7%	Development of recycling plants for plastic, paper, glass, and metal processing.
Non-Existence of Composting Programs	Organic waste buried in landfills → methane emissions	Establishment of composting facilities addressing the 50% organic waste fraction.
Insufficient Waste Composition Data	Regulatory authorities lack knowledge of waste composition.	Smartbin-generated data informing infrastructure development decisions.
Consumer Behavior Patterns	Citizens do not separate waste streams.	Public education campaigns, incentive structures, and accessible sorting tools

Table 8: Structural barriers to circular economy implementation in Algeria

Comparative Impact Analysis

Without Smartbin Data Infrastructure:

- Authorities construct inappropriate infrastructure (e.g., composting facilities in areas with low organic waste composition)

- Recycling plants receive mixed waste streams → contamination → materials become unusable
- Circular economy objectives fail due to inadequate material separation

With Smartbin Data Infrastructure:

- Data-driven infrastructure investment decisions
- Clean, sorted recyclables yield high-value market outputs
- Circular economy becomes economically viable and operationally sustainable

A Smartbin system thus represents a critical enabling technology for Algeria's transition from linear disposal practices toward circular economy principles, addressing the fundamental data gap that currently impedes effective waste management reform.

1.6. The Doughnut Economy and Its Relevance to Sustainable Development

The Doughnut Economy represents a transformative conceptual framework for sustainable development that integrates human well-being with ecological boundaries. Developed by British economist Kate Raworth, this model provides a holistic approach to economic thinking that transcends traditional growth-centric paradigms. The framework has gained significant traction in contemporary sustainability discourse, particularly for nations seeking to balance economic development with environmental preservation and social equity. For Algeria and other developing nations facing the dual challenges of resource optimization and sustainable growth, the Doughnut Economy offers a principled framework for policy development and strategic planning.

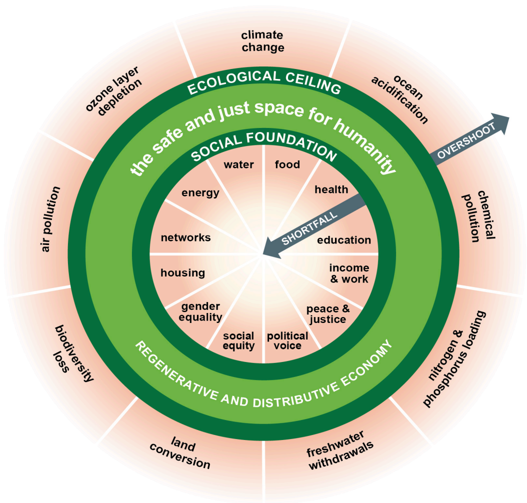

Figure 2: Doughnut Economy diagram — Social Foundation (inner ring) and Ecological Ceiling (outer ring), after Kate Raworth / Rockström et al.

The Doughnut Structure

The Doughnut Economy model consists of two concentric rings that define the safe and just space for human civilization:

1. The Social Foundation (Inner Ring): This boundary represents the minimum threshold of human well-being, encompassing essential needs including food, water, health, education, income, work, peace, justice, equity, political voice, and social community. Falling below this foundation constitutes social shortfall, indicating that human needs are not being met.
2. The Ecological Ceiling (Outer Ring): This boundary represents the planetary limits beyond which environmental degradation occurs. Based on the nine planetary boundaries framework developed by Rockström et al. (2009), this includes climate change, biodiversity loss, chemical pollution, nitrogen and phosphorus flows, ocean acidification, freshwater consumption, land-system change, ozone depletion, and atmospheric aerosol loading. Transgressing this ceiling constitutes ecological overshoot.
3. The Doughnut (Safe and Just Space): The space between these two boundaries represents the optimal zone where human needs are met without exceeding planetary capacity. This is the target zone for sustainable economic systems.

Theoretical Underpinnings

The Doughnut Economy integrates multiple theoretical traditions:

- Systems Thinking: Recognizes the interconnected nature of economic, social, and ecological systems
- Ecological Economics: Positions the economy as embedded within, rather than separate from, the biosphere
- Post-Growth Economics: Challenges the assumption that continuous GDP growth is necessary or desirable
- Stakeholder Theory: Emphasizes the interests of all stakeholders rather than prioritizing shareholders alone

Contrast with Traditional Economic Paradigms

Linear Growth Model (Traditional)

Dimension	**Traditional Growth Economy**	**Doughnut Economy**
Primary Objective	Maximize GDP growth	Thrive within planetary boundaries

Resource View	Infinite inputs	Finite planetary resources
Waste Treatment	Externalized cost	Internalized system element
Success Metric	GDP alone	Multi-dimensional well-being indicators
Time Horizon	Short-term (quarterly/annual)	Long-term (generational)
Equity Consideration	Secondary concern	Central principle

Table 9: Traditional growth model versus doughnut economy

Key Philosophical Differences

The traditional economic model operates on the assumption that economic growth is the primary solution to social problems, with environmental concerns addressed through technological innovation or market mechanisms. This approach externalizes environmental costs and treats natural resources as infinite inputs.

Conversely, the Doughnut Economy recognizes that economic activity is fundamentally embedded within ecological systems. It posits that true prosperity requires meeting human needs within the regenerative capacity of the planet. This paradigm shift necessitates rethinking core economic assumptions about value, progress, and success.

The Nine Planetary Boundaries

The ecological ceiling of the Doughnut model is grounded in scientific research identifying nine critical planetary boundaries [15]:

1. Climate Change: Measured through atmospheric CO_2 concentration (350 ppm) and radiative forcing (+1 W/m^2)
2. Biodiversity Loss: Extinction rate (<10 extinctions per million species per year)
3. Chemical Pollution: Release of toxic substances and novel entities
4. Nitrogen Flow: Industrial and agricultural nitrogen fixation (<35 million tonnes per year)
5. Phosphorus Flow: Industrial phosphorus entry into oceans (<11 million tonnes per year)

6. Ocean Acidification: Aragonite saturation state in surface waters (>80% of pre-industrial average)
7. Freshwater Consumption: Global groundwater and river use (<4,000 km^3 per year)
8. Land-System Change: Forest, grassland, and wetland conversion (<15% forest loss, <5% grassland loss)
9. Atmospheric Aerosol Loading: Particulate matter concentration affecting climate and health

Transgressing these boundaries risks triggering irreversible environmental changes with catastrophic consequences for human civilization. [16]

Application to National Development: The Algerian Context

Current Challenges

Algeria faces multiple challenges that align with Doughnut Economy principles:

Social Foundation Shortfalls:

- Regional disparities in access to quality education and healthcare
- Youth unemployment rates exceeding 25% in certain regions
- Water scarcity affecting agricultural productivity and rural livelihoods
- Need for economic diversification beyond hydrocarbon dependency

Ecological Ceiling Pressures:

- Climate change vulnerability: Rising temperatures and decreasing precipitation
- Water stress: Freshwater consumption approaching sustainable limits
- Land-system change: Urban expansion and agricultural intensification
- Biodiversity loss: Habitat degradation in Mediterranean and Saharan ecosystems
- Air pollution: Urban centers experiencing elevated particulate matter concentrations

Doughnut Economy Opportunities for Algeria

The Doughnut framework offers Algeria pathways for sustainable development:

1. Circular Economy Integration: The waste management discussed in the previous section aligns directly with Doughnut principles by maintaining materials in use and regenerating natural systems
2. Water-Smart Agriculture: Implementing irrigation efficiency and drought-resistant crops to stay within freshwater boundaries while maintaining food security
3. Renewable Energy Transition: Leveraging solar and wind resources to reduce climate change impacts while creating employment opportunities
4. Inclusive Economic Development: Diversifying beyond hydrocarbons to create jobs in manufacturing, services, and technology sectors
5. Urban Planning: Designing cities that minimize ecological footprints while maximizing social connectivity and access to services

Implementation Framework

Policy Design Principles

Effective implementation of Doughnut Economy principles requires:

1. Goal Orientation: Shift from GDP growth targets to well-being and sustainability outcomes
2. Holistic Assessment: Use multi-dimensional indicators including health, education, equality, and environmental metrics
3. Adaptive Management: Recognize complex system dynamics and employ iterative policy approaches
4. Participatory Governance: Engage diverse stakeholders in policy development and implementation
5. Long-term Perspective: Prioritize generational well-being over short-term economic gains

Measurement and Monitoring

The Doughnut Economy necessitates alternative measurement frameworks:

Traditional Indicator	**Doughnut-Aligned Alternative**
GDP growth rate	Genuine Progress Indicator (GPI)
Unemployment rate	Employment quality and security index
Inflation rate	Cost of well-being basket index
Carbon emissions per capita	Planetary boundary compliance index
Income inequality (Gini)	Multidimensional well-being distribution

Kubiszewski et al. (2013) Ecological Economics

Table 10: Doughnut-aligned alternative measurement frameworks

Institutional Requirements

Successful implementation requires:

- Cross-sectoral coordination: Breaking down ministerial silos to enable integrated policy making
- Data infrastructure: Robust systems for monitoring social and ecological indicators
- Legal frameworks: Regulations that internalize environmental costs and protect social rights
- Financial mechanisms: Investment instruments prioritizing long-term sustainability over short-term returns
- Public engagement: Education and communication strategies building societal support

Critical Analysis and Limitations

Strengths of the Doughnut Framework

1. Integrative Nature: Successfully combines social and environmental dimensions
2. Scientific Grounding: Based on empirical research on planetary boundaries
3. Practical Applicability: Provides clear visual metaphor and actionable guidance
4. Ethical Foundation: Emphasizes equity and justice as central principles
5. Flexibility: Adaptable to diverse national and local contexts

Criticisms and Challenges

1. Implementation Complexity: Translating conceptual framework into concrete policy actions remains challenging
2. Measurement Difficulties: Reliable data on all nine planetary boundaries and social foundation indicators may be unavailable
3. Political Resistance: Growth-centric paradigms remain dominant in political and economic institutions
4. Trade-off Management: Balancing competing objectives (e.g., employment vs. environmental protection) requires nuanced decision-making
5. Global Coordination: Planetary boundaries require international cooperation that may be difficult to achieve

Comparative Case Studies

Netherlands: First National Doughnut Implementation

The Netherlands has pioneered national-level Doughnut Economy implementation through:

- Doughnut Districts: Amsterdam and other cities testing local applications
- Policy Integration: Incorporating doughnut principles into national sustainability strategies
- Multi-stakeholder Collaboration: Engaging businesses, civil society, and government in co-design

Costa Rica: National Well-being Focus

Costa Rica demonstrates Doughnut-aligned development through:

- National Happiness Index: Alternative to GDP measuring well-being
- Renewable Energy: 98% renewable electricity within planetary boundaries
- Biodiversity Protection: 30% of land protected, exceeding conservation targets

Emerging Applications in Developing Nations

Countries in Africa, Latin America, and Asia are adapting Doughnut principles to address:

- Basic needs fulfillment while preventing ecological degradation
- Technology transfer for sustainable development
- International cooperation on planetary boundaries

Relevance to Waste Management and Circular Economy

The Doughnut Economy provides the overarching theoretical framework that justifies and guides circular economy implementation:

1. Social Foundation: Waste management creates employment opportunities and improves public health
2. Ecological Ceiling:Circular practices reduce resource extraction and environmental pollution
3. Systems Integration: Waste is reconceptualized as resource within closed-loop systems
4. Equity Considerations: Waste management benefits distributed across all socioeconomic groups

The SYMBIOSE Smartbin project represents a Doughnut-aligned intervention by:

- Generating data for evidence-based infrastructure investment (social foundation: effective governance)
- Enabling recycling that reduces resource extraction (ecological ceiling: reduced material flows)
- Creating employment in the recycling sector (social foundation: work and income)
- Reducing landfill methane emissions (ecological ceiling: climate change mitigation)

Circular Economy vs. Doughnut Economy

The Circular Economy and Doughnut Economy represent different but complementary approaches to sustainable development. The Circular Economy focuses on resource efficiency and waste elimination through closed-loop material systems, operating primarily at the industrial and business level. The Doughnut Economy provides a holistic framework balancing social well-being with ecological boundaries, operating at the systemic economic policy level.

For effective sustainable development, these frameworks should be integrated: the Doughnut Economy sets the ethical and strategic goals (meeting human needs within planetary boundaries), while the Circular Economy provides operational strategies (recycling, composting, reuse) for achieving environmental objectives within that framework.

In the Algerian context, waste management reform exemplifies this integration: circular economy practices (recycling, composting) achieve environmental sustainability while doughnut economy principles ensure these practices address social needs (employment, public health) and equity considerations (inclusive benefits across populations).

This complementary relationship suggests that neither framework alone is sufficient for comprehensive sustainable development. The Circular Economy without the Doughnut framework may achieve environmental efficiency while neglecting social equity. The Doughnut Economy without circular strategies may establish ethical goals while lacking practical implementation mechanisms. Their integration represents the most robust approach to achieving sustainable development in the 21st century.

1.7. Conclusion

Waste is not an endpoint. It is a design flaw in a system that still treats finite resources as infinite inputs, and Algeria is paying the price: environmentally, economically, and socially.

The data presented in this chapter leave no room for complacency. With 53.61% organic waste, 15.31% plastics, and 6.76% paper, all co-dumped in landfills or burned in incinerators, Algeria is not managing waste. It is burying and burning value. The consequences are measurable: methane emissions 25 times more potent than CO_2, soil and groundwater contamination, toxic air pollution, and landfill capacity exhaustion projected within 15–20 years. Meanwhile, a recycling rate of 5–7% places Algeria at roughly one-fifth to one-sixth of the international norm for developing countries, forfeiting hundreds of millions of dollars in recoverable materials and the employment multipliers that recycling generates.

The circular economy offers a viable alternative, but only if implemented with structural seriousness. Composting the organic fraction, recycling plastics, paper, glass, and metals, and deploying anaerobic digestion for biogas production are not aspirational concepts; they are technically proven, economically rational, and environmentally necessary. The potential is quantified: 45–50% material recovery, 50% landfill volume reduction, and job creation rates 6–10 times higher than landfilling per tonne. Yet without source separation, without recycling infrastructure, without reliable waste composition data, and without behavioral change, these potentials remain unrealized.

This is where the Doughnut Economy provides critical orientation. Kate Raworth's framework demands that economic activity operate within planetary boundaries while meeting social foundations. Algeria's current waste management violates both: it overshoots ecological limits through methane emissions and pollution, and it undershoots social needs through lost employment, public health degradation, and continued import dependency for materials that could be domestically recovered. The circular economy supplies the operational mechanisms; the Doughnut Economy supplies the ethical and systemic compass. Neither is sufficient alone.

The fundamental obstacle, however, is not technological or even primarily financial, it is informational. Authorities lack the granular, real-time waste composition data required to design appropriate infrastructure, locate facilities effectively, and monitor system performance. Without data, planning is guesswork. Without data, investment is misallocated. Without data, the circular economy cannot transition from policy document to operational reality.

Chapter 2:

Deep Learning for Intelligent Waste Classification.

2.1 Introduction

Deep learning, specifically, the capacity of neural networks to learn hierarchical representations directly from raw data, offers a pathway from data absence to data abundance. But the application is not straightforward. Generic architectures trained on ImageNet cats and dogs do not automatically transfer to the irregular, degraded, and multimodal reality of waste classification. A plastic bottle crushed under other refuse, photographed in poor lighting, partially occluded, and spectrally similar to a glass jar, presents challenges that standard computer vision pipelines are not designed to solve.

The purpose of this chapter is twofold:
(1) Establish the technical foundations of deep learning as applied to waste classification and smart monitoring systems;
(2) Demonstrate how these methods must be adapted : architecturally, computationally, and domain-specifically, to function in the constrained, real-world environment of a smart waste bin.

The chapter proceeds from machine learning fundamentals through convolutional and transformer architectures, transfer learning, object detection, and finally to edge deployment considerations that determine whether a model remains a laboratory demonstration or becomes an operational tool.

2.2 Machine Learning Preliminaries

Before examining deep learning architectures, it is necessary to situate them within the broader landscape of machine learning and to clarify why traditional methods prove insufficient for the waste classification task.

2.2.1 Supervised vs. Unsupervised Learning

Machine learning paradigms divide fundamentally based on the availability of labeled training data. Supervised learning requires input-output pairs, images of waste items annotated with their material categories (plastic, paper, organic, metal, glass). The algorithm learns a mapping function from input features to output labels by minimizing prediction error across the training set. For smartbin deployment, supervised learning is the dominant paradigm: each deposited item must be classified into a predefined category to enable downstream sorting, analytics, and circular economy routing.

Unsupervised learning operates without labeled outputs. Clustering algorithms such as k-means or Gaussian mixture models group data based on inherent similarity structures. In waste management, unsupervised methods find limited direct application for item-level classification—categories are predefined by recycling infrastructure and regulatory frameworks—but they prove valuable for anomaly detection (identifying unusual waste patterns) and for exploratory analysis of waste composition before labeled datasets are constructed.

Semi-supervised and self-supervised learning occupy intermediate positions. Semi-supervised methods leverage small labeled datasets alongside large unlabeled corpora—a realistic scenario for Algerian waste, where expert annotation is expensive but camera feeds are abundant. Self-supervised learning, particularly through contrastive pretraining, has emerged as a powerful technique for learning visual representations without manual labels, then fine-tuning on limited annotated data.

2.2.2 Classification vs. Regression in Waste Context

The smartbin system must solve both classification and regression problems. Classification assigns discrete labels: this item is plastic, that item is organic. The output is a probability distribution over material classes, and the model is trained to minimize cross-entropy loss between predicted and true distributions.

Regression predicts continuous values: fill level percentage, estimated weight, degradation rate, time-to-collection. These outputs inform logistics optimization—when to dispatch collection vehicles, how to route them, and how to balance load across the fleet. While classification dominates the academic literature on waste recognition, regression is equally critical for operational efficiency. A bin that classifies perfectly but cannot predict when it will overflow has failed in its primary function.

The distinction matters architecturally. Classification heads typically employ softmax activation over dense layers. Regression heads use linear activation and are trained with mean squared error or Huber loss. In multi-task learning frameworks, a single backbone network can feed both classification and regression heads simultaneously, sharing low-level feature representations while specializing high-level outputs.

2.2.3 Feature Extraction: Traditional vs. Learned Representations

Traditional machine learning approaches, support vector machines (SVM), k-nearest neighbors (KNN), random forests, depend on hand-engineered feature extraction. For waste images, this might involve color histograms, texture descriptors (LBP, HOG), shape metrics, or spectral signatures. The limitation is fundamental: human engineers cannot anticipate all discriminative patterns in waste imagery. A feature set designed for clean, studio-lit product photography fails when confronted with crushed, soiled, and occluded items in a bin environment.

Deep learning reverses this dependency. Convolutional neural networks learn features directly from raw pixels, discovering hierarchical patterns: edges and textures in early layers, object parts in intermediate layers, and class-discriminative structures in deep layers. This end-to-end learning eliminates the need for domain-specific feature engineering and enables the model to discover representations that human designers might never conceive. For waste classification, where intra-class variation is enormous (plastic bottles, bags, containers, and films share a material label but little visual similarity) and inter-class similarity is high (clear plastic vs. clear glass), learned representations prove substantially more robust than hand-crafted alternatives.

The empirical evidence is decisive. On standard waste classification benchmarks, deep learning approaches consistently outperform traditional ML by margins of 15–30 percentage points in accuracy. More importantly, they generalize better to unseen waste types and environmental conditions, the critical metric for deployment in diverse Algerian municipalities.

2.3 Data Types in Waste Classification

The smartbin is not merely a camera. It is a multi-sensor platform generating heterogeneous data streams, each with distinct characteristics and complementary information content. Understanding these data types is prerequisite to designing appropriate neural network architectures.

2.3.1 Image Data (RGB Camera Feeds)

RGB images constitute the primary input modality. A camera positioned above the bin inlet captures photographs of deposited items as they fall. These images provide rich spatial information: shape, color, texture, size, and contextual relationships between items. Standard resolutions range from 224×224 (for lightweight models) to 1920×1080 (for high-detail analysis).

The challenges are substantial. Lighting varies with time of day, weather, and bin location. Items are often partially occluded by other waste. Reflective surfaces (metals, glossy plastics) create specular highlights. Transparent materials (glass, clear plastic) have minimal color information. Crushed and deformed items bear little resemblance to their canonical shapes. The dataset must capture this variability, or the model will fail in deployment.

2.3.2 Spectral Data (NIR for Material Identification)

Near-infrared (NIR) spectroscopy measures how materials reflect light in the 780–2500 nm wavelength range, beyond human vision. Different materials exhibit distinct spectral signatures: plastics absorb at characteristic wavelengths, organic matter shows broad water absorption bands, and metals have high, flat reflectance. NIR sensors can distinguish materials that appear visually identical, clear PET plastic versus clear glass, or coated paper versus plastic film.

The data stream is a one-dimensional vector of reflectance values across wavelength bands. This requires 1D convolutional or fully connected architectures rather than the 2D CNNs used for images. The fusion of RGB and NIR data, combining spatial and material information, substantially improves classification accuracy, particularly for problematic categories.

2.3.3 Temporal Data (Fill-Level Time Series)

Ultrasonic or infrared time-of-flight sensors measure fill level at regular intervals, generating time-series data. These sequences reveal usage patterns: peak deposition times, seasonal variations, event-driven spikes (post-holiday, post-market-day). Long short-term memory (LSTM) networks and Transformer encoders process these sequences to predict time-to-full, optimize collection schedules, and detect anomalous patterns that might indicate illegal dumping or sensor malfunction.

Temporal data also enables indirect classification. A rapid fill sequence followed by weight increase suggests bulky organic waste (garden trimmings). Gradual, steady accumulation with periodic spikes suggests household packaging. These patterns supplement direct visual classification.

2.3.4 Multi-Modal Sensor Fusion

No single sensor modality is sufficient. RGB cameras fail on transparent and reflective materials. NIR spectroscopy lacks spatial resolution. Weight sensors cannot distinguish material types. The solution is sensor fusion: combining multiple data streams into a unified representation for classification.

Fusion architectures operate at three levels. Early fusion concatenates raw sensor inputs before processing, simple but computationally expensive and sensitive to misalignment. Intermediate fusion processes each modality through separate neural network branches, then merges learned representations at a shared layer, balancing modality-specific feature learning with cross-modal integration. Late fusion processes each modality independently and combines predictions through voting or learned weighting, modular and interpretable but potentially missing cross-modal interactions.

2.4 Deep Learning Architectures for Waste

Having established the data landscape, we now examine the neural network architectures capable of processing it. The progression from CNNs to Transformers reflects the field's evolution and the increasing complexity of waste classification requirements.

2.4.1 Convolutional Neural Networks (CNNs)

Convolutional neural networks are the foundational architecture for image-based waste classification. Their core operation, convolution, applies learnable filters across spatial dimensions, detecting local patterns (edges, textures, shapes) and composing them into increasingly abstract representations through stacked layers.

2.4.1.1 CNN Layers (Convolution, Pooling, Activation)

The convolutional layer computes dot products between input regions and learnable filter kernels, producing feature maps that highlight the presence of specific patterns. For waste classification, early filters detect edges and color blobs; intermediate filters detect object parts (bottle necks, bag handles, paper folds); deep filters encode material-specific semantics. The number of filters increases with depth, capturing richer representations.

Pooling layers (typically max-pooling) reduce spatial dimensions, providing translation invariance and computational efficiency. A crushed bottle in the corner of the image and a centered bottle activate the same high-level features after pooling. Strided convolutions increasingly replace explicit pooling in modern architectures, learning subsampling rather than hardcoding it.

Activation functions introduce non-linearity.
ReLU (Rectified Linear Unit) dominates: $f(x) = max(0, x)$
It enables gradient flow during backpropagation and induces sparse activations.
Variants: Leaky ReLU, PReLU, ELU, address the "dying ReLU" problem where negative inputs zero out permanently. For waste classification, where negative contrast features (dark shadows, transparent regions) carry discriminative information, Leaky ReLU often proves superior.

Batch normalization standardizes layer inputs, accelerating training and enabling higher learning rates. It is essential for training deep networks on waste datasets, where class imbalance and variable image quality create unstable gradient distributions.

2.4.1.2 Fully Connected Layers for Classification

After convolutional feature extraction, fully connected (dense) layers map learned representations to output predictions. The global average pooling layer—computing spatial averages of final feature maps—reduces parameters and improves generalization by enforcing feature map interpretability. Each feature map becomes a detector for a specific waste attribute, and its spatial average indicates the confidence of that attribute's presence.

The final dense layer uses softmax activation to produce class probabilities. For Algerian waste composition, the output dimension corresponds to material categories: organic (53.61% of waste stream), plastic (15.31%), paper (6.76%), glass (1.04%), metal (1.72%), hazardous (1.07%), textiles (4.5%), diapers (11.76%), and others (4.23%). These percentages from

Chapter 1 inform class weighting in the loss function, addressing the severe imbalance between dominant organic waste and rare but critical categories like hazardous materials.

2.4.2 2D-Convolution for Static Waste Images

Standard 2D convolution applies filters across height and width dimensions, assuming spatial correlation in both directions. For waste images, this is appropriate: bottle shapes, bag textures, and paper creases exhibit two-dimensional spatial structure. The receptive field, the input region influencing a single output neuron—grows with network depth and dilation rates, enabling detection of global object structures from local operations.

Dilated (atrous) convolution expands the receptive field without increasing parameters or losing resolution, valuable for detecting large waste items (cardboard boxes, textile bundles) while maintaining fine detail for small items (batteries, bottle caps). In smartbin deployment, where camera distance varies and item scales are unpredictable, multi-scale receptive fields improve robustness.

2.4.3 1D-Convolution for Spectral/Time-Series Signals

When processing NIR spectra or fill-level time series, 1D convolution operates along a single dimension. For spectral data, filters detect characteristic absorption bands, plastic peaks at 1700 nm, cellulose features in paper, water bands in organic matter. The kernel size determines spectral resolution: small kernels (3–5 bands) detect narrow peaks; large kernels (11–21 bands) capture broad trends.

For temporal data, 1D convolution detects periodic patterns (daily usage cycles) and event responses (post-deposition spikes). Causal convolution ensures predictions depend only on past and present values, not future information, essential for real-time forecasting. Dilated 1D convolution, as in the WaveNet architecture, exponentially expands temporal context without proportional parameter growth.

2.4.4 CNN Architectures Evaluated

The choice of backbone architecture determines accuracy, speed, and memory footprint trade-offs. For waste classification, four architectures represent a spectrum from accuracy-focused to efficiency-focused design.

2.4.4.1 VGG Network (Baseline, High Parameter Count)

VGGNet, introduced by Simonyan and Zisserman in 2014, established the principle of deep, uniform architecture: stacks of 3×3 convolutions with periodic 2×2 max-pooling. VGG-16 (13 convolutional layers, 3 dense layers, ~138 million parameters) and VGG-19 (16 convolutional layers) serve as baselines.

For waste classification, VGG's simplicity is pedagogically valuable but practically limiting. Its 138 million parameters demand substantial memory and computation. The fully connected layers (4096 neurons each) are prone to overfitting on limited waste datasets. Yet VGG's hierarchical feature visualization, showing how early layers detect edges and deep layers detect object parts, provides interpretability valuable for debugging misclassifications. In the Algerian context, where initial datasets may be small, VGG serves as a baseline to demonstrate the necessity of more efficient architectures.

2.4.4.2 ResNet (Skip Connections, Deeper Training)

ResNet, introduced by He et al. in 2015, solved the degradation problem: as networks deepen, accuracy saturates and then degrades, not from overfitting but from optimization difficulties. ResNet's solution is the residual block: instead of learning a direct mapping H(x), the network learns a residual $F(x) = H(x) - x$, with the identity mapping x propagated via skip connections.

This reformulation enables training of networks with 50, 101, or 152 layers. For waste classification, deeper networks capture more nuanced material distinctions—the subtle differences between HDPE and PET plastics, or between coated and uncoated paper. ResNet-50 (~25.6 million parameters) and ResNet-101 (~44.5 million parameters) are standard choices. The bottleneck design (1×1, 3×3, 1×1 convolutions) reduces computation while maintaining representational capacity.

In smartbin deployment, ResNet's depth improves accuracy but increases inference time. The trade-off must be evaluated empirically: does the 3% accuracy gain from ResNet-101 over ResNet-50 justify the 40% latency increase? For high-contamination waste streams where misclassification has environmental costs, the answer may be yes.

2.4.4.3 Xception (Depthwise Separable Convolutions, Efficiency)

Xception, proposed by Chollet in 2017, extends the Inception hypothesis: cross-channel correlations and spatial correlations can be decoupled. Standard convolution mixes channels and spatial dimensions simultaneously. Depthwise separable convolution splits the operation: depthwise convolution applies a single filter per input channel, and pointwise convolution (1×1) combines channels.

This factorization reduces parameters and computation dramatically. Xception (~22.8 million parameters) achieves accuracy comparable to ResNet-101 with lower computational cost. For waste classification, where real-time inference is required at the edge, Xception's efficiency is compelling. The architecture also captures fine-grained spatial patterns, critical for distinguishing crumpled paper from plastic film, or identifying contamination on otherwise clean recyclables.

2.4.4.4 MobileNet / EfficientNet (Edge Deployment Constraints)

MobileNetV3 and EfficientNet represent the state of the art in accuracy-efficiency trade-offs. MobileNetV3 employs hardware-aware neural architecture search (NAS), optimizing for latency on mobile CPUs through inverted bottlenecks, squeeze-and-excitation modules, and h-swish activations. EfficientNet scales network width, depth, and resolution jointly via compound scaling, achieving superior accuracy with fewer parameters than ResNet.

For smartbin deployment, these architectures are essential. A Raspberry Pi 4 or Coral TPU has a limited compute budget. MobileNetV3-Large achieves 75.2% ImageNet top-1 accuracy with only 5.4 million parameters. EfficientNet-B0 achieves 77.3% accuracy with 5.3 million parameters. On waste datasets, fine-tuned EfficientNet models often reach 90%+ accuracy while maintaining inference times under 50ms on edge hardware, fast enough for real-time user feedback.

The choice is not merely technical but political: deploying ResNet-152 on cloud servers requires constant connectivity, creating dependencies on infrastructure that may be unreliable in Algerian municipalities. Edge-capable models enable autonomous operation, data sovereignty, and deployment in remote areas.

2.4.5 Transformers for Waste Classification

Transformers, originally developed for natural language processing, have revolutionized computer vision through the Vision Transformer (ViT) and its variants. Unlike CNNs, which process local neighborhoods, Transformers model global relationships from the first layer through self-attention mechanisms.

2.4.5.1 Vision Transformers (ViT): Global Attention for Spatial Waste Features

ViT splits images into fixed-size patches (typically 16×16 pixels), linearly embeds each patch, adds positional encoding, and processes the sequence through standard Transformer encoder blocks. Self-attention computes pairwise relationships between all patches, enabling the model to attend globally to relevant regions.

For waste classification, this global attention is powerful. A plastic bottle occluded by a paper bag may be partially visible in several patches; self-attention integrates these fragmented cues across the image. The model also learns which patches are discriminative, effectively performing soft attention without explicit localization mechanisms.

However, ViT requires large datasets for pretraining. Without sufficient data, it underperforms relative to CNNs. For Algerian waste, where labeled datasets are initially limited, this is a significant constraint. Fine-tuning from ImageNet-pretrained ViT models partially addresses this, but the domain gap between natural images and waste imagery remains.

2.4.5.2 Hybrid CNN-Transformer Architectures

Hybrid architectures combine CNN local feature extraction with Transformer global modeling. Models like CoAtNet, BoTNet, and CvT use convolutional stem layers to process raw images, then feed feature maps into Transformer blocks. This approach leverages CNNs' inductive biases (translation equivariance, local correlation) for early feature learning while employing Transformers' global receptive fields for high-level reasoning.

For waste classification, hybrids offer the best of both worlds: the efficiency and data efficiency of CNNs for low-level features, and the relational modeling of Transformers for complex, occluded scenes. CvT (Convolutional Vision Transformer) replaces patch embedding with convolutional tokenization, progressively merging tokens while maintaining spatial structure. This proves particularly effective for waste images where object boundaries are irregular and contextual relationships (item-on-item occlusion) are common.

2.4.6 Attention Mechanisms Beyond Transformers

Even within purely CNN architectures, attention modules improve waste classification by recalibrating feature importance.

2.4.6.1 Convolutional Block Attention Module (CBAM)

CBAM sequentially applies channel and spatial attention. Channel attention uses global average and max pooling to produce a channel-wise weight vector, emphasizing informative feature maps (e.g., those detecting plastic textures) and suppressing irrelevant ones. Spatial attention uses pooled features across channels to produce a spatial attention map, focusing on discriminative regions (e.g., the label area of a bottle) while ignoring background clutter.

For waste classification, CBAM improves performance on contaminated and occluded items. A banana peel partially covering a plastic bottle creates spatial confusion; CBAM's attention mechanism can downweight the occluding region and upweight visible bottle features. The module adds minimal parameters (~0.1% overhead) and is plug-and-play with any CNN backbone.

2.4.6.2 Squeeze-and-Excitation (SE) for Channel Recalibration

SE blocks, introduced by Hu et al. in 2018, perform channel-wise feature recalibration. The squeeze operation aggregates spatial information through global average pooling. The excitation operation learns per-channel weights through a bottleneck of fully connected layers. These weights scale channel activations, adaptively emphasizing informative features.

In waste classification, SE blocks help the model focus on material-discriminative channels. For distinguishing paper from plastic, channels encoding texture roughness and light transmission are more important than color channels (both materials can be white). SE recalibration amplifies these discriminative channels without human intervention. SE-ResNet and SE-EfficientNet variants consistently outperform their base counterparts on waste benchmarks.

2.5 Transfer Learning and Domain Adaptation

Training deep networks from scratch requires millions of labeled examples, prohibitively expensive for waste classification. Transfer learning leverages knowledge from large, general datasets and adapts it to specific domains.

2.5.1 Pre-trained Models on ImageNet

ImageNet (1.28 million images, 1000 classes) provides the standard pretraining corpus. Models trained on ImageNet learn generic visual representations, edge detectors, texture filters, shape templates, that transfer remarkably well to waste classification. Even though ImageNet contains no waste categories, the low-level and mid-level features are universal.

The transfer process involves freezing early layers (which contain generic features) and fine-tuning later layers (which contain task-specific features) on the waste dataset. For limited data, aggressive freezing prevents overfitting. For larger datasets, full fine-tuning yields better adaptation. Learning rate scheduling is critical: pre-trained layers use small learning rates (1e-5 to 1e-4) to preserve general knowledge; newly initialized layers use larger rates (1e-3 to 1e-2) to learn task specifics.

2.5.2 Fine-Tuning on Waste Datasets (TACO, TrashNet, WasteNet)

Several public waste datasets facilitate transfer learning. TrashNet contains 2527 images across six categories (cardboard, glass, metal, paper, plastic, trash). TACO (Trash Annotations in Context) provides 1500 images with instance-level annotations for object detection. WasteNet and similar datasets expand coverage and image counts.

These datasets have limitations. They are predominantly Euro-American in content: packaging designs, product types, and contamination patterns differ from Algerian waste. Camera setups, lighting, and backgrounds are often studio-controlled. Fine-tuning on these datasets provides a starting point but not a solution. The model must be further adapted to local conditions through continued training on Algerian-specific data.

2.5.3 Domain Shift: Euro-American Datasets to Algerian Waste Realities

Domain shift, the performance degradation when models trained on one data distribution are applied to another, is severe in waste classification. Algerian waste differs in packaging types (local brands, Arabic script labels), material prevalence (higher organic fraction, different plastic types), contamination levels (higher moisture and soil content in organic waste), and environmental conditions (dust, extreme temperatures, variable infrastructure).

Domain adaptation techniques address this. Unsupervised domain adaptation (UDA) uses labeled source data and unlabeled target data to learn domain-invariant features. Adversarial methods (DANN, ADDA) train a feature extractor to confuse a domain discriminator, forcing features that are indistinguishable between source and target. Self-training and pseudo-labeling generate synthetic target labels for iterative refinement.

2.5.4 Synthetic Data Generation (GANs for Algerian Waste Augmentation)

Data augmentation, rotations, flips, color jittering, noise injection—increases effective dataset size but cannot create fundamentally new waste types. Generative Adversarial Networks (GANs) can. A GAN consists of a generator network that creates synthetic images and a discriminator network that distinguishes real from fake. Through adversarial training, the generator learns to produce increasingly realistic waste images.

Conditional GANs (cGANs) generate images from specific class labels, enabling controlled augmentation of rare categories. StyleGAN and its variants produce high-resolution, diverse images. For waste classification, GAN-generated images of underrepresented categories, hazardous waste, specific plastic types, local packaging, can balance training data without physical collection.

However, GAN-generated data carries risks. Mode collapse produces limited diversity. Artifacts in generated images may confuse the classifier. The most effective approach combines GAN augmentation with real data, using synthetic samples to expand variety but validating on purely real test sets. For Algerian waste, where certain categories are rare but critical (hazardous materials at 1.07%), GANs offer a pathway to robust classification without waiting for years of natural data accumulation.

2.6 Object Detection for Smartbin Deployment

Classification assigns a single label to an image. Object detection localizes and classifies multiple items within a “scene essential” when users deposit multiple waste items simultaneously, or when items overlap and occlude each other in the bin.

2.6.1 YOLO Family (Real-Time Multi-Object Detection)

You Only Look Once (YOLO) revolutionized object detection by framing it as a single regression problem: predicting bounding boxes and class probabilities simultaneously from a single network evaluation. YOLOv5, YOLOv7, and YOLOv8 offer progressively improved accuracy-speed trade-offs, with YOLOv8 introducing anchor-free detection and decoupled heads.

For smartbin deployment, YOLO's real-time capability is decisive. A user deposits waste; the camera captures the scene; YOLO detects each item, localizes it with a bounding box, and classifies it, all within 10–30ms on modern GPUs, 50–100ms on edge devices. This enables immediate feedback: a display indicating "Plastic: 2 items, Paper: 1 item, Organic: 1 item" guides users toward correct separation and educates through reinforcement.

The anchor-free design of YOLOv8 is particularly suited to waste, where object aspect ratios vary enormously: long plastic bags, flat cardboard sheets, round bottles, irregular organic matter. Predefined anchor boxes (as in earlier YOLO versions) poorly capture this variability; anchor-free detection learns object shapes directly from data.

2.6.2 SSD and Single-Shot Detectors

Single Shot MultiBox Detector (SSD) and its variants (RetinaNet, EfficientDet) also perform detection in a single pass. SSD uses multiple feature maps at different scales to detect objects of varying sizes, with default boxes (aspect ratio priors) at each location. RetinaNet addresses class imbalance through focal loss, downweighting easy background examples and focusing training on hard, misclassified objects.

For waste detection, where small items (batteries, bottle caps) and large items (cardboard boxes, bags) coexist, multi-scale detection is essential. EfficientDet achieves state-of-the-art accuracy through compound scaling and BiFPN (Bidirectional Feature Pyramid Network) feature fusion, though at a higher computational cost than YOLO. The choice depends on hardware: YOLO for edge-constrained smartbins, EfficientDet for cloud-connected systems with GPU acceleration.

2.6.3 Handling Occlusion, Clutter, and Variable Lighting in Bin Environments

The smartbin environment is adversarial. Items are dropped from above, creating unpredictable orientations and collisions. Multiple items land simultaneously, occluding each other. Lighting depends on time of day and bin location, with shadows cast by the bin structure itself. Dust and residue on the camera lens degrade image quality.

Robust detection requires architectural and data strategies. Architecturally, feature pyramid networks (FPN) preserve fine detail for small, occluded items while maintaining semantic information for large items. Data augmentation with heavy occlusion simulation, random lighting variation, and synthetic noise trains the model for worst-case conditions. Test-time augmentation (TTA), averaging predictions across multiple image transformations, improves reliability at the cost of inference time.

For the Algerian context, additional challenges include dust storms (reducing visibility), extreme temperatures (affecting sensor performance), and power fluctuations (impacting camera exposure). The model must be validated under these conditions, not merely in laboratory settings.

2.7 Edge AI: Model Compression for Embedded Deployment

A model that runs perfectly on a laboratory GPU is useless if it cannot execute on the smartbin's embedded hardware. Edge AI, the deployment of neural networks on resource-constrained devices, is the bridge between research and operation.

2.7.1 Quantization (INT8, FP16)

Neural networks typically use 32-bit floating-point (FP32) weights and activations. Quantization reduces precision to 16-bit floating-point (FP16) or 8-bit integer (INT8), halving or quartering memory and computation. INT8 quantization, in particular, enables deployment on integer-optimized hardware (ARM NEON, Coral TPU, NVIDIA TensorRT).

Post-training quantization converts a trained FP32 model to INT8 without retraining, using calibration on representative data to determine optimal quantization parameters. Quantization-aware training (QAT) simulates quantization during training, allowing the network to adapt to reduced precision. For waste classification, QAT typically recovers 1–2% accuracy lost in post-training quantization.

The impact is substantial. An EfficientNet-B0 model quantized to INT8 reduces from 20MB to 5MB and achieves 2–4× inference speedup on edge hardware. For a smartbin processing hundreds of depositions daily, this determines whether classification is real-time or batch-processed.

2.7.2 Pruning (Structured vs. Unstructured)

Pruning removes redundant parameters. Unstructured pruning zeroes individual weights, creating sparse matrices that require specialized hardware for efficient execution. Structured pruning removes entire channels, filters, or layers, producing dense, smaller networks that run on standard hardware.

For smartbin deployment, structured pruning is preferred. A 50% channel-pruned ResNet-50 runs on any standard processor; a 90% unstructured sparse model requires sparse tensor libraries that may not be available on embedded platforms. Iterative pruning—train, prune, fine-tune, repeat, gradually reduces model size while maintaining accuracy. Lottery ticket hypothesis research suggests that overparameterized networks contain sparse subnetworks capable of matching full network performance if trained in isolation.

2.7.3 Knowledge Distillation

Knowledge distillation transfers knowledge from a large, accurate teacher model to a small, efficient student model. The student is trained not only on ground-truth labels but on the teacher's soft predictions (probability distributions), which encode richer information about class similarities. A student learning that a plastic bottle is 0.7 plastic, 0.2 glass, 0.1 metal gains more than from a hard label of "plastic."

For waste classification, distillation enables deployment of MobileNet-sized models with ResNet-level accuracy. The teacher might be an ensemble of large models trained on extensive data; the student is a lightweight network trained to mimic the ensemble. This is particularly valuable when the student must run on a Raspberry Pi or microcontroller while the teacher operates in the cloud during development.

2.7.4 Hardware Targets: Raspberry Pi, NVIDIA Jetson, Coral TPU

The choice of edge hardware determines model constraints and deployment strategy.

Raspberry Pi 4 (4GB RAM, ARM Cortex-A72): Runs TensorFlow Lite and ONNX models. Suitable for quantized MobileNetV3 or EfficientNet-Lite. Inference time: 100–300ms per image. Power: 5–7W. Cost: ~$75. Limitation: no GPU acceleration for neural networks.

NVIDIA Jetson Nano / NX (128-core Maxwell / 384-core Volta GPU): Supports CUDA and TensorRT. Runs larger models (ResNet-50, YOLOv5s) with GPU acceleration. Inference time: 30–80ms. Power: 5–15W. Cost: $150–$400. Limitation: higher cost and power consumption.

Google Coral TPU (Edge TPU coprocessor): Purpose-built for INT8 quantized models. Runs MobileNet and EfficientNet at 10–30ms. Power: 2–5W. Cost: ~$100 (with dev board). Limitation: requires full INT8 quantization; limited model support.

2.8 Deep Learning vs. Traditional ML in Waste Classification

Support Vector Machines with hand-engineered HOG features achieve 60–70% accuracy on waste datasets. K-Nearest Neighbors with color histograms achieves 50–60%. Random Forests with combined feature sets reach 65–75%. These methods require domain expertise for feature design, fail on novel waste types, and degrade under variable conditions.

Deep learning approaches substantially outperform them. A fine-tuned ResNet-50 achieves 85–92% on the same datasets. EfficientNet-B3 reaches 90–95%. With multi-modal fusion and attention mechanisms, 95%+ is achievable. The margin is not incremental; it is transformative. For a system where misclassification sends recyclable plastic to landfill or hazardous waste to composting, accuracy is not a metric but an environmental imperative.

The comparison is not merely about accuracy but about scalability. Traditional ML requires new feature engineering for each new waste category, each new camera, each new country. Deep learning requires only data: collect images, annotate, fine-tune. For Algeria's waste management reform, where categories may evolve and deployment must scale across dozens of municipalities, this scalability is essential.

2.9 Conclusion

This chapter has traversed the technical landscape from machine learning fundamentals to edge deployment, with a consistent focus on the specific requirements of waste classification in resource-constrained, real-world environments. Several conclusions emerge with clarity.

First, deep learning is not optional for intelligent waste management. The complexity of waste imagery, occlusion, contamination, variable lighting, irregular shapes, exceeds the capacity of hand-engineered features and traditional classifiers. The accuracy gap of 15–30 percentage points between deep learning and traditional methods translates directly into environmental performance: more recyclables recovered, less contamination, longer landfill lifespan.

Second, architecture selection must be driven by deployment constraints, not benchmark leaderboard position. ResNet-152 wins ImageNet competitions but fails in a solar-powered bin in Tlemcen. EfficientNet, MobileNet, and their quantized variants are the practical choices for edge deployment, where every millisecond and milliwatt matters.

Third, transfer learning and domain adaptation are essential bridges. Models trained on Euro-American datasets require substantial adaptation for Algerian waste realities. The smartbin itself must become a data collection and labeling instrument, progressively improving its own training corpus through operation.

Fourth, sensor fusion and attention mechanisms address the inherent ambiguity of waste classification. No single sensor modality is sufficient; the integration of RGB, NIR, weight, and temporal data through multi-modal architectures provides the robustness required for operational deployment.

Finally, edge AI is not a technical preference but a political and infrastructural necessity. Cloud-dependent systems create vulnerabilities in connectivity, data sovereignty, and cost. Edge-capable models enable autonomous operation in remote areas, protect sensitive waste data, and align with the Doughnut Economy's emphasis on localized, resilient systems.

Chapter 3:

Contribution and proposed solution.

3.1 INTRODUCTION

While national statistics provide macro-level understanding of waste composition, effective automated sorting requires granular, context-specific recognition of individual waste items as they appear in real Algerian households.

This chapter presents the complete development pipeline of SYMBIOSE, a custom object detection system designed specifically for Tlemcenian municipal waste. The work follows a methodological progression from data collection through model training to performance evaluation, with particular attention to the challenges of domain adaptation in a developing-country context.

The chapter is organized as follows. Section 3.2 describes the tools and platforms employed throughout the project. Section 3.3 details the pretrained household trash model and the critical gap observed when testing Algerian data. Section 3.4 presents the SYMBIOSE dataset construction, including the unconventional street-trash collection methodology and its implications for data representativeness. Section 3.5 covers the training pipeline and architectural choices. Section 3.6 reports quantitative results with per-class analysis. Section 3.7 discusses limitations and proposes future improvements.

3.2 TOOLS AND PLATFORMS

3.2.1 LabelImg: Manual Annotation Foundation

The annotation pipeline began with LabelImg, an open-source graphical image annotation tool widely used in computer vision projects. LabelImg operates offline, generating Pascal VOC format XML files or YOLO format text files containing bounding box coordinates and class labels.

The manual annotation process proceeded as follows:

1. Image loading: Raw photographs were loaded individually into the LabelImg interface
2. Bounding box creation: For each waste object visible in the image, a rectangular bounding box was drawn tightly around the object boundaries
3. Class assignment: Each box was assigned one of five predefined classes: aluminum, cardboard, glass, non-recyclable, or plastic

4. File export: Annotations were saved in YOLO format, producing .txt files with the structure: <class_id> <center_x> <center_y> <width> <height>

This manual approach, while labor-intensive, ensured high-quality annotations with precise object localization. The author personally annotated all 560 images, developing intimate familiarity with the visual characteristics of each waste category. This direct engagement with the data proved invaluable for later understanding model failure modes.

However, LabelImg presented several limitations for collaborative and scalable annotation:
- No cloud synchronization or team sharing capabilities
- No built-in quality control or review mechanisms
- Manual file management across folders
- No automatic augmentation or dataset versioning

These limitations motivated the transition to a more robust platform for dataset management and augmentation.

3.2.2 Roboflow: Dataset Management and Augmentation

Roboflow was adopted as the primary dataset management platform, serving three critical functions:

- Dataset Import and Conversion: The manually annotated images and YOLO-format labels were uploaded to Roboflow, which automatically validated annotation integrity, detected potential issues (missing labels, incorrect formats), and standardized the dataset structure.
- Version Control: Roboflow's versioning system enabled systematic dataset iteration. Version 1 contained the original 560 images. Version 2 incorporated platform-level augmentations, generating approximately 1,680 training images through geometric and photometric transformations.
- Export Flexibility: The platform supported multiple export formats, including YOLOv11, enabling seamless integration with the Ultralytics training pipeline.

The augmentation strategy applied in Version 2 included:
- Horizontal flipping (50% probability)
- Vertical flipping (10% probability)
- Rotation (plus/minus 15 degrees)
- Brightness adjustment (plus/minus 20%)
- Gaussian blur (up to 2 pixels)
- Random noise (up to 2%)
- Random cropping (0-10%)
- Cutout (2 boxes, 10% size)

These augmentations were selected specifically to address anticipated real-world variations in Algerian waste photography: diverse lighting conditions, camera angles, and partial occlusions characteristic of informal waste handling.

3.2.3 Google Colab: Cloud-Based Training Infrastructure

Model training was conducted on Google Colab, a cloud-based Jupyter notebook environment providing free access to NVIDIA GPUs. The Tesla T4 GPU (14,913 MiB VRAM) enabled feasible training of the YOLOv11m architecture, which would be prohibitively slow on CPU-only infrastructure.

Colab's ephemeral nature session timeout after 90 minutes of inactivity and maximum 12-hour runtime introduced workflow constraints. Models had to be saved to Google Drive periodically to prevent loss of training progress. This limitation, while manageable, underscored the resource constraints typical of student and independent research in developing countries, where access to dedicated GPU servers or cloud computing credits may be limited.

3.2.4 Ultralytics YOLOv11: Detection Architecture

The Ultralytics YOLOv11 framework provided the underlying object detection implementation. YOLOv11 introduces architectural refinements over previous iterations, including:
- Enhanced C2f modules for improved feature extraction
- Decoupled detection head separating classification and regression tasks
- Optimized anchor computation
- Integrated training-time augmentations (mosaic, mixup, auto-augment)

The "m" (Medium) variant was selected as a compromise between detection accuracy and computational efficiency, with 20,033,887 parameters and 67.7 GFLOPs.

3.3 THE PRETRAINED MODEL AND THE ALGERIAN GAP

3.3.1 Household Trash Pretrained Model

Before developing SYMBIOSE, we investigated existing waste detection solutions by training a YOLOv11m model on a large-scale household trash dataset comprising approximately 15,000 images. This dataset, sourced from Kaggle, contained generic waste items photographed primarily in North American and European contexts.

The training configuration for this baseline model followed standard practices:

```
model = YOLO('yolo11m.pt')
results = model.train(
    data='household_trash.yaml',
    epochs=50,
    batch=16,
    imgsz=640,
    optimizer='AdamW',
    lr0=0.001,
)
```

The model achieved reasonable performance on its target domain, demonstrating the feasibility of waste detection when training and test data share similar visual characteristics.

3.3.2 Testing on Algerian Data: The Domain Gap

To assess transferability to the Algerian context, we collected an initial test set of Algerian household waste products and evaluated the pretrained model. Results were disappointing: detection accuracy approached zero for most Algerian items.

This failure was not attributable to model architecture limitations but rather to a fundamental domain gap between the training data and Algerian reality.
The following factors were identified:

- Packaging Localization: Algerian consumer products feature distinct packaging designs, brand logos, and color schemes absent from Western datasets.
  For example:
- Local packings use distinctive plastic containers with Arabic and French bilingual labeling.
- Soft drinks (Selecto, Hamoud, L'Exquise) employ recognizable but locally specific bottle designs.
- Typography and Language: Product labels incorporate Arabic script, which the pretrained model had never encountered. The visual texture of Arabic calligraphy, connected letters, right-to-left orientation, and distinct geometric patterns represents a fundamentally different visual feature space from Latin script.
- Product Categories: Certain waste categories dominant in Algeria are rare or absent in Western datasets.
- Socioeconomic Context: The prevalence of certain materials reflects Algerian consumption patterns. Glass bottles are more common for beverages due to deposit-return systems, while plastic bags remain ubiquitous for informal retail despite regulatory restrictions.

3.3.3 Implications for Model Development

The Algerian gap demonstrated that no amount of transfer learning from generic waste datasets could bridge the domain divide. A custom dataset, collected specifically from Algerian consumption and waste streams, was essential for any viable detection system.

This observation aligns with broader critiques of AI deployment in developing countries, where models trained on Western data systematically fail when applied to local contexts. The "digital colonialism" critique wherein AI systems are designed for and by the Global North, then inadequately adapted for the Global South finds concrete illustration in waste detection. The SYMBIOSE project thus represents not merely a technical contribution but a methodological stance: AI systems for local problems require local data.

3.4 THE SYMBIOSE DATASET: CONSTRUCTION AND CHARACTERISTICS

3.4.1 Data Collection Methodology

The SYMBIOSE dataset was constructed through a multi-source collection strategy designed to capture the diversity of Tlemcenian household waste while maintaining practical feasibility for a student researcher.

Source 1: Street Trash Photography

The primary and most unconventional data source was street-collected waste. We physically photographed discarded packaging and products from municipal waste accumulation points in urban Tlemcen. This methodology provided several unique advantages:

- Real-world degradation: Items exhibited authentic wear, soiling, crushing, and weathering conditions absent from pristine product photography
- Post-consumption state: Packaging showed actual usage patterns (empty bottles, torn bags, crushed cans)
- Demographic representativeness: Street trash reflects actual consumption patterns across socioeconomic strata, not merely the author's household

The street collection process was systematic: We visited multiple waste accumulation points during different times of day and week, photographing all visible waste items without selection bias. This approach is justified by the public nature of the waste and the research objective of understanding actual waste streams.

Source 2: Friend and Family Networks

To supplement street collection, we requested waste items from two friends and one family member, representing 3 different household compositions and consumption patterns:

- Friend 1: Family of 3 adults, high consumption of processed foods and beverages
- Friend 2: Family with children, diverse product range including baby products and snacks
- Family member: Traditional household, emphasis on local products and bulk purchases

This network approach expanded the product diversity beyond the author's personal consumption while maintaining the Algerian context. The collected items were photographed in controlled conditions before disposal.

3.4.2 Sybiose Dataset Composition and Class Distribution

The final dataset comprises 560 original images across five classes:

Class	Instances	Primary sources	Visual characteristics
Plastic	115	Bottles, bags, containers	Diverse colors; transparent and opaque
Cardboard	51	Boxes, packaging, tubes	Brown/tan; printed labels; folded states
Glass	45	Bottles, jars	Transparent; reflective; green/clear/brown
Aluminum	55	Cans, foil, trays	Metallic; crushed and uncrushed
Non-recyclable	6	Mixed materials; soiled items	Heterogeneous; no consistent features

Table 11: Composition of SYMBIOSE dataset by class

The class distribution is highly imbalanced, with plastic dominating and non-recyclable severely underrepresented. This imbalance reflects the reality of Algerian waste composition: plastic packaging constitutes the majority of household waste by volume, while truly non-recyclable items (mixed materials, heavily soiled packaging) are relatively rare.

3.4.3 The Asymmetry Problem and Its Virtue

The SYMBIOSE dataset is asymmetric by design and this asymmetry constitutes both a limitation and a methodological strength.

The Limitation: Machine learning models perform poorly on imbalanced datasets. The scarcity of non-recyclable instances (6 versus 115 for plastic) prevents robust learning of that category. The model will be biased toward predicting plastic, and evaluation metrics will be dominated by plastic performance.

The Virtue: Unlike most academic datasets, which are artificially balanced to facilitate algorithmic comparison, SYMBIOSE reflects actual waste stream composition. National statistics from Chapter 1 indicated that plastic constitutes approximately 15-20% of municipal waste by weight, while mixed non-recyclable materials represent a smaller fraction. The dataset's imbalance mirrors this reality.

This representativeness is methodologically significant. Most waste detection datasets in the literature are collected from:

- Controlled laboratory settings with pristine products
- Curated online image collections
- Artificially balanced sampling

These datasets produce models that perform well on benchmark tests but fail in real deployment because they do not reflect actual waste stream distributions. SYMBIOSE's asymmetry, while complicating model training, ensures that successful detection translates to real-world applicability.

Future Correction: Now that we have realistic data, we are working on expanding underrepresented categories (particularly non-recyclable and aluminum) to improve model robustness. However, this expansion is being studied carefully rather than simply adding data from unrealistic conditions to reach artificial robustness. Our goal is to build a model that will behave correctly in the real world, so we will maintain the proportional relationship to actual waste composition rather than artificially equalizing classes.

3.4.4 Annotation Quality and Challenges

Manual annotation with LabelImg revealed several category-specific challenges:

- Plastic versus Glass: Transparent plastic bottles (e.g., water bottles) and glass bottles share visual similarity, particularly when crushed or photographed with glare. Annotation required careful attention to material-specific cues: glass thickness, refraction patterns, and weight-implied rigidity.
- Aluminum versus Plastic: Uncrushed aluminum cans and plastic bottles of similar shape (e.g., soft drink containers) were occasionally confused. The metallic sheen of aluminum versus the matte or glossy finish of plastic served as discriminative features.

- Non-recyclable Definition: The "non-recyclable" category required subjective judgment. Items with mixed materials (plastic-coated paper, foil-lined bags) or heavy soiling were classified as non-recyclable based on local recycling facility capabilities. This definition may vary across municipalities and over time as recycling technology improves.

3.5 TRAINING PIPELINE AND ARCHITECTURAL DECISIONS

3.5.1 Two-Stage Transfer Learning Strategy

The training strategy employed two-stage transfer learning to maximize performance with limited data:

Stage 1: Domain Pretraining
- Base model: COCO-pretrained YOLOv11m
- Target: Large household trash dataset (approximately 15,000 images)
- Objective: Learn generic waste detection features (shapes, materials, degradation patterns)
- Duration: 50 epochs, approximately 4 hours on Tesla T4

Stage 2: Target Fine-Tuning
- Base model: Stage 1 output (best_household_trash.pt)
- Target: SYMBIOSE dataset (560 to 1,680 augmented images)
- Objective: Adapt to Algerian-specific waste categories
- Duration: 100 epochs (early stopped at 79, best at 59), approximately 2.4 hours

This two-stage approach was motivated by the extreme scarcity of Algerian waste data.

Direct training from COCO to SYMBIOSE would require the model to simultaneously learn:
(a) what waste looks like in general, and
(b) Algerian-specific variations. With only 560 images, this dual learning task is infeasible.

The intermediate household trash stage provides a "waste-aware" feature representation that the Algerian stage need only specialize.

3.5.2 Backbone Freezing

Given the small dataset size, 10 layers of the backbone were frozen during Stage 2. This decision was based on the following reasoning:

- Early convolutional layers learn generic features (edges, textures, colors) that transfer across domains
- Later layers learn object-specific features that require adaptation
- With 560 images, full network training risks overfitting and catastrophic forgetting
- Freezing preserves the "waste detection knowledge" from Stage 1 while allowing the head to learn Algerian categories

The frozen backbone effectively constrains the model to use its pretrained visual vocabulary rather than learning new low-level features from limited data.

3.5.3 Hyperparameter Configuration

The fine-tuning configuration was optimized for small-dataset adaptation:

Parameter	Value	Rationale
Learning rate	0.0005	Half of standard to prevent destroying weights
Optimizer	AdamW	Stable for fine-tuning with weight decay
Weight decay	0.0005	Prevents overfitting on small dataset
Batch size	16	Maximum fitting T4 GPU memory
Image size	640×640	Standard YOLO resolution
Loss weights	box=7.5, cls=0.5, dfl=1.5	Emphasize localization accuracy
Early stopping	20 epochs	Prevent overtraining on plateaued metrics
Warmup epochs	3	Gradual adaptation from frozen to trainable

Table 12: SYMBIOSE fine-tuning hyperparameter configuration

3.5.4 Data Augmentation Strategy

Augmentation was applied at two levels:

Roboflow Augmentation (Offline): Generated 3x dataset expansion through geometric and photometric transforms. This creates actual new training images with modified visual content.

YOLO Training Augmentation (Online): Applied during each epoch:
- Mosaic: Combines 4 images into composite training samples
- MixUp: Blends two images with alpha compositing
- Copy-Paste: Transfers objects between images
- HSV shifts, flips, rotation, scaling, shearing, perspective distortion

The dual augmentation strategy effectively increases the visual diversity experienced by the model beyond the raw image count.

3.6 RESULTS AND QUANTITATIVE ANALYSIS

3.6.1 Overall Performance Metrics

The final model achieved the following performance on the SYMBIOSE validation set:

Metric	Value	Interpretation
mAP50	52.4%	Moderate detection at forgiving IoU threshold
mAP50-95	34.8%	Lower precision at strict localization criteria
Precision	64.5%	When model predicts, 64.5% are correct
Recall	49.0%	Model finds 49% of all actual objects

Table 13: SYMBIOSE overall performance metrics

The mAP50 of 52.4% indicates that the model successfully localizes and classifies approximately half of all waste objects under the standard 0.5 IoU criterion. This performance is comparable to small-scale waste detection benchmarks in the literature, though substantially below industrial deployment thresholds (typically greater than 80%).

The 18-percentage-point gap between mAP50 and mAP50-95 (52.4% vs. 34.8%) reveals a localization precision problem: the model often detects the correct object class but with imprecise bounding box boundaries. This is characteristic of small datasets where the model learns approximate locations rather than exact boundaries.

3.6.2 Per-Class Performance Breakdown

Class	Precision	Recall	AP50	AP50-95	Assessment
Plastic	72.0%	73.0%	72.1%	48.7%	Strong
Glass	57.5%	57.8%	61.8%	37.3%	Moderate
Non-recyclable	73.1%	46.2%	53.3%	39.0%	Moderate
Cardboard	70.3%	37.1%	44.6%	29.9%	Poor
Aluminum	49.8%	30.9%	30.6%	18.9%	Poor

Table 14: Per-class performance breakdown

Plastic is the standout performer, with both high precision and high recall. This reflects the class's visual distinctiveness, large training sample, and relative homogeneity within the category.

Glass performs surprisingly well given the transparency challenge. The model likely relies on contextual cues (bottle shape, cap presence, liquid contents) and edge refraction patterns rather than surface texture.

Aluminum is the critical failure mode. The 30.6% AP50 indicates that the model misses approximately 70% of aluminum objects or misclassifies them. The low recall (30.9%) suggests the model is particularly conservative in aluminum detection.

3.6.3 Analysis of Aluminum Failure

The aluminum underperformance stems from multiple factors:

1. Visual confusion with plastic: Uncrushed aluminum beverage cans closely resemble plastic bottles in shape and size. Both are cylindrical with printed labels. The metallic sheen aluminum's distinguishing feature is often obscured by lighting, angle, or image compression.

2. Shape variability: Aluminum objects exhibit extreme deformation: uncrushed cans (tall cylinders), crushed cans (irregular flattened shapes), foil sheets (amorphous), and trays (shallow rectangles). This variability exceeds the model's capacity to learn a unified "aluminum" representation.

3. Limited training data: With only 55 instances (versus 115 for plastic), the model receives insufficient exposure to aluminum's visual diversity.

4. Reflective surface properties: Aluminum's specular reflection creates inconsistent appearance across lighting conditions, complicating feature learning.

3.6.4 Cardboard Underperformance

Cardboard's moderate precision (70.3%) but poor recall (37.1%) indicates a conservative detection strategy: when the model predicts cardboard, it is usually correct, but it frequently misses cardboard instances. This pattern suggests:

- Cardboard is confused with background textures (wood, paper, fabric)
- Flattened cardboard boxes lose their distinctive 3D structure
- Printed designs on cardboard vary widely, preventing consistent feature learning

3.6.5 Non-Recyclable: Better Than Expected

The "non-recyclable" category, despite its inherent heterogeneity, achieved 53.3% AP50 better than both cardboard and aluminum. This counterintuitive result may reflect:

- The model learning to detect "non-recyclable" as a residual category: if an object is not clearly plastic, glass, cardboard, or aluminum, it is classified as non-recyclable
- The small sample size (6 instances) may have produced an optimistically biased estimate
- Certain non-recyclable items (e.g., styrofoam) have distinctive visual textures that are easily learned

3.6.6 Training Dynamics and Convergence

Training was monitored through 79 epochs before early stopping triggered:

- Loss convergence: Box, classification, and DFL losses decreased monotonically, indicating stable optimization
- Validation plateau: mAP50-95 peaked at epoch 59 and remained stable, suggesting the model had extracted all learnable information from the dataset
- Precision-recall trade-off: Precision decreased from 67.8% (epoch 67) to 49.4% (epoch 76) while recall increased from 38.6% to 48.5%, indicating the model became less selective but more comprehensive

The 20-epoch patience window without improvement suggests that additional training would not yield significant gains without additional data.

3.7 LIMITATIONS AND FUTURE PERSPECTIVES

3.7.1 Current Limitations

Dataset Scale: The 560-image dataset is insufficient for robust deep learning. Contemporary object detection benchmarks typically employ 10,000 to 100,000+ images per class. The limited scale constrains model capacity and generalization.

Class Imbalance: The factor-of-19 disparity between plastic (115 instances) and non-recyclable (6 instances) creates severe learning bias. The model is effectively optimized for plastic detection at the expense of rare categories.

Category Definition: The "non-recyclable" class functions as a semantic residual rather than a visually coherent category. This fundamental design flaw limits learnability regardless of data quantity.

Image Resolution: 640x640 input may be inadequate for small objects (e.g., bottle caps, foil fragments) and fine boundary localization.

Environmental Diversity: The dataset lacks systematic variation in lighting (night, indoor artificial, outdoor shadow), camera quality, and background clutter.

No Temporal Context: Real-world waste sorting involves sequential video frames, conveyor belt motion, and human interaction cues. Static image detection ignores this rich contextual information.

3.7.2 Immediate Improvements (Short-Term)

1. Dataset Expansion and Rebalancing

Target: 2,000 to 5,000 images with proportional representation reflecting but not exaggerating actual waste stream composition. Priority additions:

- Aluminum: 200+ additional images emphasizing crushed/uncrushed variation, different brands, and lighting conditions
- Cardboard: 150+ images including flattened, torn, and wet states
- Non-recyclable: Restructure into visually coherent subcategories (styrofoam, chip bags, mixed materials, contaminated items) rather than a single residual class

2. Resolution Increase

Experiment with 1280x1280 input resolution to improve small object detection and boundary precision. Trade-off: increased computational cost and memory requirements.

3. Architecture Scaling

Evaluate YOLOv11l (Large) and YOLOv11x (Extra Large) variants. With expanded data, larger models may capture more nuanced feature distinctions, particularly for aluminum-plastic differentiation.

4. Advanced Augmentation

Implement CutMix, GridMask, and domain randomization to increase effective dataset diversity. Consider synthetic data generation using 3D rendering of Algerian product packaging.

3.7.3 Medium-Term Developments

1. Active Learning Pipeline

Implement uncertainty-based sampling to prioritize annotation of images where the model is most confused. This maximizes information gain per annotation effort, critical given limited labeling resources.

2. Multi-Modal Integration

Combine visual detection with:
- Weight sensors: Differentiate aluminum (light) from glass (heavy)
- Spectroscopy: Material-specific spectral signatures for plastic type identification
- Audio: Crushed aluminum versus plastic produce distinct sounds

3. Temporal and Contextual Modeling

Extend from static image detection to video-based tracking on conveyor belts. Recurrent architectures or transformer-based temporal models could leverage motion cues and object persistence.

4. Edge Deployment Optimization

Convert the trained model to TensorRT or ONNX formats for deployment on embedded systems (NVIDIA Jetson, Raspberry Pi with Coral TPU). Optimize for real-time inference on low-power devices suitable for Algerian recycling facility infrastructure.

3.7.4 Long-Term Vision

1. National Waste Detection Network

Scale from household-level detection to municipal waste characterization. Deploy camera-equipped collection vehicles or stationary sensors at landfill and transfer stations to generate real-time waste composition analytics.

2. Circular Economy Integration

Link detection outputs to:
- Product barcode databases for manufacturer accountability
- Recycling facility capacity and pricing for optimal routing
- Consumer feedback applications for waste reduction education

3. Policy Support Tool

Provide municipal governments with granular, data-driven waste composition evidence to inform:
- Extended producer responsibility regulations
- Deposit-return system design
- Import restriction policies for non-recyclable packaging

3.8. THEORETICAL PROTOTYPE: SYMBIOSE SMART BIN

3.8.1 Design Genesis and Methodology

The theoretical prototype presented in Figure 3 represents the culmination of the SYMBIOSE project's vision for an integrated, intelligent waste management system. We created the design through a hand-drawn sketch on paper, to conceptualize the spatial and functional relationships between the system's components. This initial sketch was subsequently processed through Google's Gemini AI to refine the visual rendering and enhance structural clarity. The final illustration was then edited using Canva to achieve the polished, annotated presentation shown in Figure 3.

This iterative design process from manual sketching to AI-assisted refinement to graphic editing reflects the resource constraints typical of academic research in developing-country institutions. The absence of industrial design software or professional prototyping services necessitated creative adaptation of freely available tools.

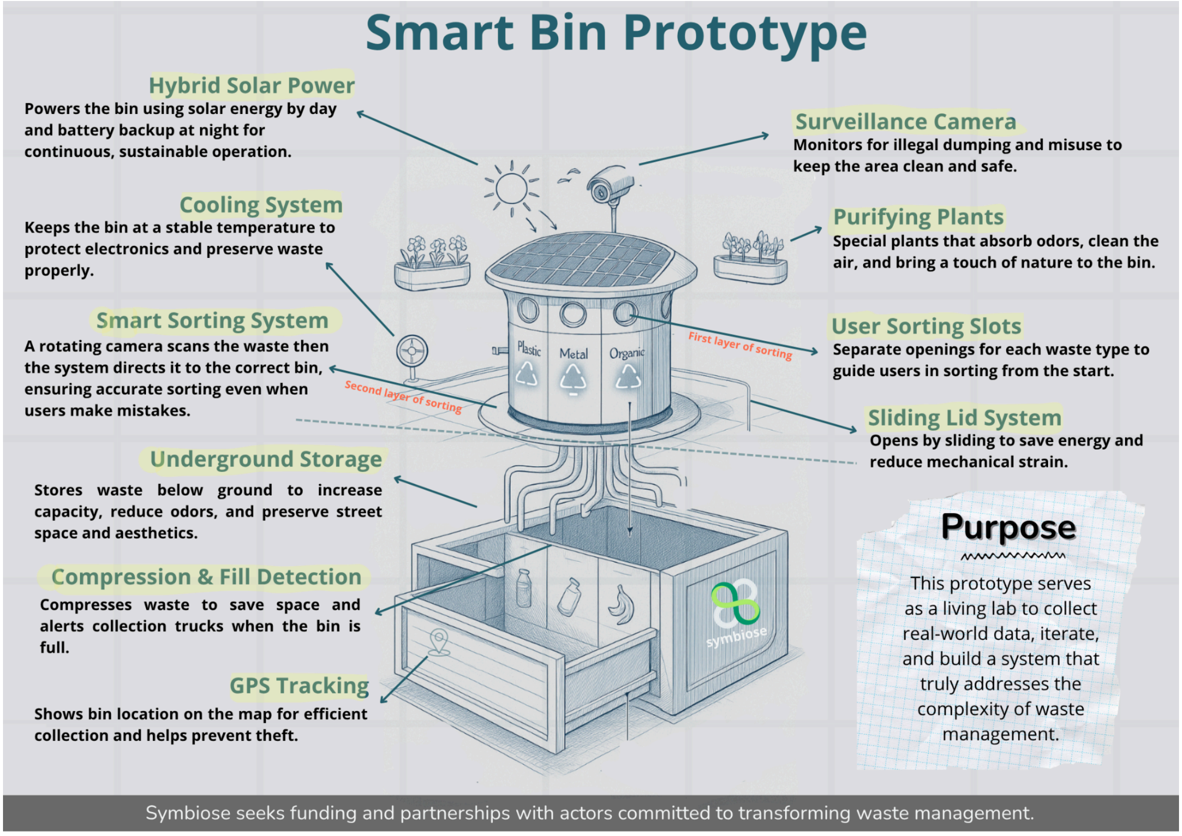

Figure 3: Representation of the Prototype SYMBIOSE smartbin.

3.8.2 System Architecture and Component Description

The Smart Bin Prototype integrates multiple subsystems into a unified waste management station, as detailed below:

Hybrid Solar Power System

The prototype incorporates photovoltaic panels mounted on the bin's upper surface, providing primary energy supply during daylight hours. A battery backup system ensures continuous operation during nighttime periods or low-irradiance conditions. This design choice addresses Algeria's abundant solar resources while ensuring grid-independent operation in areas with unreliable electrical infrastructure.

Surveillance Camera Module

A mounted camera provides real-time monitoring of the waste deposition area, serving dual functions: (1) detection of illegal dumping and system misuse, and (2) potential future integration with computer vision for automated waste recognition at the point of disposal. The surveillance capability addresses persistent challenges in public waste management regarding accountability and behavioral monitoring.

User Sorting Slots (First Layer of Sorting)

The upper section features dedicated openings for distinct waste categories: Plastic, Metal, and Organic. This manual pre-sorting interface guides users toward correct waste segregation at the point of disposal, reducing contamination rates in subsequent automated processing stages. The physical separation at intake represents a human-in-the-loop design philosophy that acknowledges current limitations in fully automated sorting accuracy.

Smart Sorting System (Second Layer of Sorting)
A rotating camera array positioned below the intake slots performs automated visual inspection of deposited waste. The system directs items to the correct internal compartment based on visual classification, providing a secondary correction mechanism for user sorting errors. This two-layer architecture, manual primary sorting with automated secondary verification, balances user engagement with technological capability.

Cooling System
An integrated thermal management subsystem maintains stable internal temperature, protecting electronic components from thermal degradation and preserving organic waste in a controlled environment prior to collection. Temperature stability is particularly critical in Algeria's climatic conditions, where ambient temperatures frequently exceed 40°C during summer months.

Purifying Plants
The prototype incorporates biophilic design elements through the integration of air-purifying vegetation. These plants serve multiple functions: odor absorption, air quality improvement, and aesthetic enhancement that promotes public acceptance of waste infrastructure. The inclusion of natural elements represents an innovative approach to mitigating the "not-in-my-backyard" (NIMBY) syndrome commonly associated with waste facilities.

Sliding Lid System
The access mechanism employs a sliding rather than hinged design, reducing mechanical complexity and energy consumption during operation. This design choice extends component lifespan and minimizes maintenance requirements in resource-limited deployment contexts.

Underground Storage
The lower section extends below ground level, significantly increasing storage capacity without expanding the above-ground footprint. This subterranean design reduces odor emission at street level, preserves urban aesthetics, and minimizes the spatial intrusion of waste infrastructure in densely populated areas.

Compression and Fill Detection
An integrated compaction mechanism reduces waste volume, extending the interval between collection operations. Fill-level sensors transmit capacity data to municipal collection services, enabling optimized routing and scheduling of collection vehicles. This data-driven approach to logistics represents a significant efficiency improvement over fixed-schedule collection systems.

GPS Tracking

Location tracking capability enables real-time monitoring of bin position and status, facilitating efficient fleet management and theft prevention. The geospatial data layer supports municipal planning and resource allocation decisions.

3.9.3 Innovation and Patent Potential

Two subsystems within the Smart Bin Prototype exhibit particularly strong potential for intellectual property protection:

Circular Camera System for Automated Sorting
The rotating camera array positioned beneath the intake slots represents a novel mechanical configuration for waste inspection. Unlike existing static-camera sorting systems, the circular arrangement enables multi-angle visual capture without requiring object movement or conveyor mechanisms. This design reduces mechanical complexity while improving classification accuracy through multi-viewpoint analysis. The integration of this camera system with the SYMBIOSE detection model creates a complete hardware-software solution with significant commercial potential.

Plant-Integrated Air Purification System
The incorporation of vegetation into waste containment infrastructure represents an underexplored domain at the intersection of biophilic design and environmental engineering. The specific configuration of plant species selection, irrigation systems, and airflow management within a waste bin context constitutes a potentially patentable innovation. Preliminary research indicates that certain plant species (e.g., Chlorophytum comosum, Spathiphyllum) demonstrate effective volatile organic compound absorption in enclosed environments, suggesting technical feasibility.

3.8.4 Implementation Constraints and Institutional Limitations

Despite the theoretical viability of the Smart Bin Prototype, physical construction has not been realized due to resource constraints at the University of Tlemcen. The following factors have prevented prototype fabrication:

Financial Constraints
The estimated material and manufacturing costs for a functional prototype exceed the available research funding. Component procurement, including solar panels, camera systems, servo motors for the sliding mechanism, compression actuators, and sensor arrays, requires capital investment beyond current departmental budgets.

Fabrication Infrastructure
The University of Tlemcen lacks dedicated prototyping facilities. Access to external fabrication services would require additional funding for transportation and contracting.

Technical Support

The prototype's mechanical and electrical systems require specialized expertise in mechatronics, power electronics, and embedded systems programming. Our main focus on this project was on finding a real solution to the waste waste problem.

3.9.5 Future Development Pathway

The theoretical prototype serves as a design specification for future implementation, contingent upon securing external funding or institutional partnerships. The following development pathway is proposed:

-Phase 1: Component Procurement and Subsystem Testing (Estimated duration: 6 months)
- Source solar panels, battery systems, and power management electronics
- Procure camera modules and develop embedded vision pipeline
- Test compression mechanism with representative waste materials

Phase 2: Mechanical Assembly and Integration (Estimated duration: 4 months)
- Fabricate bin structure using locally available materials
- Install underground storage compartment
- Integrate mechanical subsystems (sliding lid, compression, sorting gates)

Phase 3: Software Integration and Field Testing (Estimated duration: 6 months)
- Deploy SYMBIOSE detection model on embedded hardware
- Calibrate camera system and sorting mechanism
- Conduct field trials in controlled municipal environment

Phase 4: Patent Application and Commercialization (Estimated duration: 12 months)
- File provisional patents for circular camera system and plant-integrated purification
- Engage with municipal authorities for pilot deployment
- Explore manufacturing partnerships for scaled production

3.8.6 Conclusion

The Smart Bin Prototype represents the hardware realization of the SYMBIOSE project's software capabilities. While physical construction remains unrealized due to institutional resource constraints, the detailed design specification provides a foundation for future implementation upon securing external funding. The patentable innovations identified within the prototype, particularly the circular camera system and plant-integrated air purification, offer potential pathways for commercialization that could support continued research and development.

The prototype's design philosophy was based on a study market, it emphasizes sustainability (solar power, biophilic elements), user engagement (manual sorting slots, aesthetic integration), and operational efficiency (automated sorting, compression, data-driven logistics). These principles align with Algeria's national waste management objectives while addressing the specific infrastructural and climatic challenges of the North African context.

3.9 CONCLUSION

This chapter presented the complete development of SYMBIOSE, a YOLOv11-based waste detection system specifically designed for Algerian household recycling. The work addressed the critical domain gap between generic waste detection models and local Algerian consumption patterns through custom data collection, two-stage transfer learning, and culturally informed category design.

The achieved performance of 52.4% mAP50 with significant per-class variation demonstrates both the feasibility and current limitations of deep learning for Algerian waste management. The aluminum detection failure and class imbalance issues provide concrete directions for improvement.

Most significantly, the dataset collection methodology combining street waste photography with household network sampling produced a representationally authentic dataset that mirrors actual Algerian waste streams. This authenticity, while complicating algorithmic optimization, ensures that successful improvements translate directly to real-world deployment.

The SYMBIOSE project thus contributes not only a technical artifact but a methodological template: AI development for local problems requires local data, local expertise, and explicit attention to domain-specific visual cultures. The Algerian gap observed in generic pretrained models is not a technical failure but a design failure one that this work begins to address.

Chapter 4:

Business Model Canva.

4.1. Introduction

For the Symbiose project, the Business Model Canvas was adapted to reflect the realities of smart waste management in Algeria. Symbiose is more than a simple smart bin, it combines artificial intelligence, mechatronics, circular economy principles, and social inclusion into an integrated ecosystem. The solution not only improves waste sorting efficiency at the source but also creates economic value by transforming recyclable waste into a profitable resource while promoting environmental sustainability.

Unlike conventional waste management systems, Symbiose creates value for several stakeholders simultaneously. Institutions benefit from cleaner environments and automated monitoring, citizens experience a more hygienic and user-friendly disposal system, and recycling actors receive higher-quality sorted materials. Furthermore, by integrating informal waste collectors into a structured collection network, the project contributes to both social and environmental objectives.

The following sections present each component of the Business Model Canvas and explain how they contribute to the viability and scalability of the Symbiose business model.

4.2. Customer Segments

Although Symbiose is designed to improve waste management for the general public, its direct customers are organizations capable of purchasing, deploying, and managing the smart waste management infrastructure.

a) Are we aiming to reach a broader clientele?

Yes. Symbiose is initially designed for institutional and organizational customers because they possess the financial capacity and operational responsibility required to deploy smart waste management systems. Nevertheless, the solution has been conceived with scalability in mind and can progressively expand to serve a broader range of public and private organizations throughout Algeria and the MENA region.

b) What are our priority customer segments?

The primary customer is:

- APC (People's Municipal Assembly): Municipal authorities are the principal customers because they are responsible for urban cleanliness, public waste collection, and environmental management. They can deploy Symbiose in public spaces to improve waste collection efficiency while supporting municipal sustainability objectives, and benefiting financially from its valorization.

Other potential customer include:

- Universities and Higher Education Institutions: Universities represent an ideal early adopter due to their controlled environments, high population density, and growing commitment to sustainable campus initiatives. They can install Symbiose across faculties, libraries, student residences, and common areas while using the platform to monitor waste generation and environmental performance, and get financial benefit from it.

- Businesses and Commercial Establishments: Hotels, restaurants, shopping centers, office buildings, and large companies can adopt Symbiose to improve waste management practices, enhance their environmental image, and generate additional value from recyclable materials.
- Public Institutions: Hospitals, administrative buildings, cultural centers, and other public facilities represent potential customers due to their continuous waste production and increasing environmental responsibilities.

c) Who ultimately makes the purchasing decision?

Although the end users are citizens, students, employees, and visitors who interact with the smart bins on a daily basis, purchasing decisions are generally made by the organizations responsible for managing the facilities and allocating financial resources.

For municipal deployments, the purchasing decision is primarily made by the APC or the relevant local authorities responsible for waste management and public infrastructure.

For university deployments, purchasing decisions are typically made by the university administration or rectorate, which manages institutional budgets and distributes funding to faculties, departments, and student residences. These governing bodies evaluate investment decisions based on operational efficiency, sustainability objectives, and long-term financial benefits.

As Symbiose primarily targets institutional customers rather than individual consumers, its commercialization strategy relies on direct communication and strategic partnerships instead of mass marketing. The objective is to establish long-term collaborations with organizations responsible for waste management and environmental sustainability.

4.3. Channels

The main channels for Symbiose are the following:

Direct Sales

Direct sales constitute the primary commercialization channel. Meetings and presentations can be organized with municipal authorities (APCs), university administrations, and managers of public or private institutions to demonstrate the technical capabilities and environmental benefits of the system. This approach enables decision-makers to evaluate the solution according to their operational needs and budgetary constraints.

Demonstration Projects and Pilot Installations

Pilot projects represent an effective channel for introducing Symbiose to potential customers. Installing prototype smart bins in university campuses or selected public areas allows stakeholders to observe the system's performance under real operating conditions. These demonstrations also provide valuable data regarding waste sorting efficiency, user engagement, and operational improvements before larger-scale deployment.

Institutional Partnerships

Strategic partnerships with universities, municipalities, environmental organizations, and recycling companies facilitate the dissemination and adoption of the solution. Such collaborations increase the project's credibility while creating opportunities for joint environmental initiatives and sustainable development programs.

Digital Communication

A professional website and the social media platforms “Linkedin” and “Facebook” will be used to present the project's objectives, technological features, environmental impact, and pilot project results. Digital communication also provides a platform for sharing educational content related to recycling, circular economy principles, and sustainable waste management practices.

Academic and Professional Events popular events

Participation during the next 12 months in :

- The innovation competition Algeria Startup Challenge (ASC)
- The entrepreneurship show Startup Academy
- The environmental exhibition “Djazaïr Khadraa”
- The biggest technology event in Algeria “Algeria 2.0”

These activities provide additional opportunities to showcase Symbiose to investors, institutional partners, and public authorities, and increase the visibility of the project while facilitating networking with potential collaborators.

Overall, the proposed channels combine direct institutional engagement with digital communication and strategic partnerships, ensuring effective dissemination of the solution while supporting its long-term scalability.

4.4. Customer Relationships

Symbiose is designed as a long-term technological solution rather than a one-time product purchase, maintaining strong relationships with institutional customers is essential to ensure successful implementation, continuous operation, and customer satisfaction.

The relationship strategy for Symbiose focuses on collaboration, technical support, and continuous improvement.

Personalized Assistance

Each customer organization has different operational requirements depending on its size, waste generation patterns, infrastructure and location. Consequently, Symbiose offers:

- A personalized study to understand the unique waste patterns and problems of the clients.
- Support during the planning, installation, and configuration phases.

Technical Support and Maintenance

Continuous technical assistance is essential for maintaining system reliability. Customers receive maintenance services in case of updates, troubleshooting, and hardware inspections to ensure uninterrupted operation of the smart bins and the associated monitoring platform.

Long-Term Partnerships

Rather than pursuing isolated sales, Symbiose aims to establish long-term partnerships with municipalities, universities, and other institutions. These collaborations aim for continuous deployment, periodic system upgrades, and the integration of additional smart waste management services as customers need to evolve.

Performance Monitoring and Feedback

The digital platform enables customers to monitor waste collection statistics, recycling performance, and system utilization through real-time dashboards. Regular feedback sessions with customers allow the project team to identify improvement opportunities and adapt the solution according to operational requirements.

Environmental Awareness and User Engagement

Beyond serving institutional customers, Symbiose seeks to strengthen relationships with end users by promoting responsible waste disposal behaviors and advocate for more efficient regulations. Educational campaigns, awareness programs, and recycling initiatives will be organized in September-December 2026 during the annual plantation and cleaning campaigns done by :

- YouthLed Algeria
- Djazaïr Khadraa
- The Facebook communities “Les Tlemcenophiles”, “OSMAT”, “S.O.S l'antiquité Tlemcen l'authenticité”.

To increase user participation and awareness, maximize the environmental impact of our advocacy and build a notorious public image.

In summary, the customer relationship strategy combines personalized support, continuous technical assistance, long-term institutional collaboration, and user engagement. This approach not only improves customer satisfaction but also contributes to the sustainable adoption and continuous improvement of the Symbiose smart waste management system.

4.5. Key Partners

Key partners are the organizations and stakeholders that contribute essential resources, expertise, or services required for the successful implementation and operation of the business model. Since Symbiose integrates artificial intelligence, smart technologies, and waste management within a circular economy framework, collaboration with multiple partners is necessary to ensure both technical feasibility and long-term sustainability.

The principal partners identified for the Symbiose project are presented below.

Municipal Authorities (APCs)

The People's Municipal Assemblies (APCs) constitute one of the most important strategic partners. They are responsible for urban waste management, public sanitation, and the installation of waste collection infrastructure within municipalities. Their collaboration is essential for authorizing the deployment of smart bins in public spaces, facilitating waste collection operations, and supporting environmental initiatives at the local level.

Universities and Educational Institutions

Universities serve as both customers and strategic partners. Beyond purchasing and deploying the solution, they provide suitable environments for pilot implementations, research activities, and user evaluation. Academic institutions can also contribute scientific expertise, encourage student participation, and promote environmental awareness campaigns that support sustainable waste management.

Recycling Companies

Recycling companies represent key operational partners by collecting and processing the recyclable materials sorted by Symbiose. Their collaboration ensures that separated waste is effectively reintegrated into the recycling value chain, thereby supporting the principles of the circular economy while generating additional economic value.

Technology Suppliers

The development and maintenance of Symbiose requires reliable suppliers of electronic components and technological equipment, including sensors, microcontrollers, cameras, communication modules, power systems, and mechanical components. These suppliers ensure the availability of high-quality hardware necessary for the construction and continuous operation of the smart bins.

Software and Cloud Service Providers

Cloud computing services, data storage solutions, and software development tools are required to support the artificial intelligence algorithms, remote monitoring platform, database management, and real-time communication between smart bins and administrators. These technological partners contribute to the reliability, scalability, and security of the digital infrastructure.

Maintenance and Technical Service Providers

Specialized maintenance partners assist in equipment installation, preventive maintenance, hardware replacement, and technical troubleshooting. Their involvement helps maintain system reliability while minimizing operational downtime.

Environmental Organizations and Government Agencies

Environmental associations and governmental institutions promoting sustainable development can support Symbiose through awareness campaigns, collaborative projects, environmental certifications, or funding opportunities. Their participation strengthens the project's social impact while encouraging wider adoption of sustainable waste management practices.

Through these strategic partnerships, Symbiose benefits from complementary expertise, operational support, technological resources, and institutional collaboration, thereby increasing the feasibility and long-term sustainability of its business model.

4.6. Key Activities

Symbiose combines intelligent hardware, artificial intelligence, software services, and waste management, its activities extend beyond product development to include continuous monitoring, maintenance, and customer support.

The principal activities required for the successful operation of Symbiose are as follow:

Research and Development

Continuous research and development activities are necessary to improve the system's performance, lower costs, optimize models, and integrate emerging technologies. These activities include enhancing waste recognition accuracy, improving sorting mechanisms, and developing new functionalities according to customer feedback and technological advancements.

Design and Manufacturing of Smart Bins

One of the core operational activities involves designing, assembling, and testing the intelligent waste bins. This process includes integrating sensors, cameras, electronic components, mechanical sorting mechanisms, and communication systems to ensure reliable operation under real-world conditions.

Software Development and Platform Management

The project requires the continuous development and maintenance of its digital platform, which enables remote monitoring, data visualization, system management, and performance analysis. Software updates and cybersecurity measures are also essential to guarantee system reliability and protect collected data.

Installation and Deployment

Before becoming operational, each Symbiose system must be installed, configured, and tested at the customer's premises. Deployment activities are :

- site assessment
- equipment installation
- system calibration
- clear instructions for the user

Waste Monitoring and Data Analysis

Symbiose continuously collects operational data regarding waste generation, bin fill levels, sorting accuracy, and recycling performance. Analyzing these data allows customers to optimize waste management strategies while supporting evidence-based environmental decision-making.

Policy and Regulations

In addition to technological operations, Symbiose engages in current climate change, waste management and AI ethics discussions, promotes responsible waste disposal through awareness campaigns, educational workshops, and sustainability initiatives organized in collaboration with partners already mentioned. These activities encourage behavioral change and maximize the environmental impact of the project.

Collectively, these key activities enable Symbiose to deliver an integrated smart waste management solution that combines technological innovation, operational efficiency, environmental sustainability, and continuous customer support.

4.7. Charges and Costs

1. Initial Investment Costs (One-time, DZD)

Expense Item	Description	Estimation (DZD)

Prototype R&D & Hardware	Camera, sensors, rotary motors, recycled structural materials	100,000 – 150,000
Electronic/Mechatronic Assembly	Custom engineering setup & structural casing	80,000 – 120,000
Ethical/Green Cloud Hosting (1 yr)	Secure IoT cloud infrastructure & AI model hosting	50,000 – 80,000
UI/UX & Dashboard Development	Web/Mobile metrics interface for clients/operators	40,000 – 70,000
Legal, Ethics, & Incorporation	Registering the social enterprise/startup	30,000 – 50,000
Total Estimated Upfront Cost		**300,000 – 470,000**

Table 15: Initial investment costs for SYMBIOSE

2. Monthly Estimated Operating Expenses (Moderate Scenario)

- Embedded Systems/Mechatronics Engineer: 40,000 DZA
- Data Engineer (AI/Computer Vision): 40,000 DZA
- Ecology & Circular Economy Expert: 40,000 DZA
- Commercial/Sales Executive: Commission-based per sale
- Community Manager / Marketing Lead: TBD / Stipend (~15,000 - 20,000 DZA)
- Accountant / Financial Expert: Project-basis/Retainer (~10,000 - 15,000 DZA)
- Ethical Cloud & Server Maintenance: ~10,000 DZA

Total Estimated Monthly Expenses: ~155,000 – 175,000 DZA

3. Estimated Revenue Streams & Net Profits (Monthly / Pilot Phase Projections)

Revenue Assumption: Subscriptions from multi-level residences/businesses for smartbin optimization services + profit-sharing yields from aggregated high-purity recyclable materials (PET, cardboard, metal) sold to formal regional processing plants.

Pilot Scale : 10 strategic smartbin units deployed across university residencies and local businesses): Estimated Monthly Inflows: 200,000 – 300,000 DZD (Subscription + Valorized Waste Re-sales)

Estimated Monthly Expenses: ~165,000 DZD

Estimated Net Profit: ~35,000 – 135,000 DZD / month (Scaling rapidly as units deployed increase).

b) What are the most important costs?

- Human capital (specialized R&D salaries for mechatronics and AI engineering).
- Hardware procurement for building initial functional smartbin units.
- Ethical cloud computing and telemetry infrastructure.

c) How to reduce costs or improve efficiency?

- Leverage open-source frameworks and academic cloud credits (via University of Tlemcen/incubation programs).
- Source structural parts from recycled/local materials to keep hardware CapEx low.
- Rely on organic digital growth and community outreach via Youth-Led Algeria to minimize traditional marketing ad spend.
- Structure initial sales via commission to mitigate early fixed payroll risks.

4.8 Revenue Streams

a) What products or services are our clients ready to pay for?

Waste Management SaaS Subscription: Monthly optimization fee paid by institutions, residences, and hotels for real-time bin monitoring, predictive logistics, and ESG dashboard access.

Premium Waste Aggregation Sales: Bulk sales of high-purity, perfectly sorted recyclable materials (untouched by informal degradation) sold directly to formal industrial recyclers.

b) By what means do we generate revenue?

Waste Optimization Subscription : Recurring monthly software & telemetry fee paid by property managers/businesses to manage their ecological footprint.

High-Purity Recyclables Sales : Direct B2B sale of pristine, separated raw materials to formal recycling plants. A negotiated portion of this revenue is routed back to the host facility/residence as an incentive rebate.

c) What is our pricing model?

For Institutional Clients / Businesses / Residences:

- Smartbin Deployment: Covered under an operational SaaS optimization subscription tier + hardware service agreement.
- Financial Rebate Model: 20-30% of the raw value of the valorized waste collected on their site is credited back to them (either as a discount on their SaaS fee or a direct payout), incentivizing high sorting compliance.

For Recyclers (B2B Buyers):

- Premium market rate for aggregated, source-separated, contamination-free raw materials (PET, paper/cardboard, metal).

4.9 Conclusion

The Business Model Canvas outlined in this section establishes a structured, highly viable strategic framework for launching Symbiose in Tlemcen. By synchronizing source-separation technology with an inclusive social enterprise framework, formalizing informal waste collectors, rewarding institutional clients financially, and rebranding waste into an industry people want to work in, we solve deep-rooted municipal inefficiencies. The integration of local AI, mechatronic error-correction, and circular economics aims for both the technical feasibility and strong economic potential of turning regional waste streams into dignified green opportunities.

Business Model Canvas

SYMBIOSE

KEY PARTNERS

- **Informal Waste Workers:** Integrating them by transitioning them from precarious street/dumpster diving into formal roles.
- **Youth-Led Algeria:** Non-profit organization providing volunteers, eco-activists, and young talents to help with community onboarding, educational campaigns, and social equity advocacy.
- **University of Tlemcen & i2e center :** testing grounds.
- **BET E³:** Environmental engineering consulting and validation.
- **APC Tlemcen:** municipal support.
- Local Private Recyclers.

KEY ACTIVITIES

- Building and assembling the physical prototype, integrating cameras for computer vision, and building the sorting/rotative correction mechanism.
- Data collection and model training.
- Marketing and branding
- Policy & Ethics Consulting

KEY RESOURCES

- Data collection on local waste.
- Source sorting smartbin.
- Partnership with local recycling plants and industrial byers.
- Specialized expertise in waste management, data science, computer vision, and mechanical design.

VALUE PROPOSITIONS

- **Waste Valorization:** Clients receive a direct percentage/rebate from the revenue generated by the sorted, high-value waste collected from their premises.
- **Zero-Odor :** Solves the primary pain point of traditional sorting by using closed, smart mechanisms that eliminate bad odors, to get high user compliance.
- **Sort-at-Source:** Hardware uses an internal corrective mechanism to guarantee perfectly sorted recyclables, reducing downstream sorting costs.
- **Regulatory & ESG Compliance:** Helps universities and government entities comply with Algeria's national integrated waste management strategies (SNGID 2035) and Extended Producer Responsibility (EPR) laws.

CUSTOMER RELATIONSHIP

- **Co-Creation & Piloting:** test prototypes risk-free.
- Consulting & Policy Advisory
- Continuous Support & Transparency:

CHANNEL

- **Direct B2B/B2G Outreach:** Direct consultations and system demonstrations with APC directors, university rectors, and residence directors.
- Digital Campaigns and Ethical AI Branding.

CUSTOMER SEGMENTS

- **Municipalities &** Government: APC of Tlemcen seeking to hit national zero-waste and pollution-reduction targets.
- **Local Businesses:** Restaurants and hotels looking to turn their high volume of daily waste into an additional revenue stream rather than just a disposal cost.
- **Multi-Level Residences & Large building complexes:** They benefit financially from valorization while using Symbiose as a premium selling point (cleanliness and modern waste management acts as a rare, highly attractive luxury amenity in Tlemcen).

COST STRUCTURE

- R&D and prototyping
- **Cloud Hosting:** Subscription for green/ethical cloud storage and computing infrastructure to process the computer vision AI.
- **Team Salaries (Monthly):**
  - Embedded Systems/Mechatronics Engineer: 40,000 DZA
  - Data Engineer (AI/Computer Vision): 40,000 DZA
  - Waste Management Ecologist : 40,000 DZA
  - Commercial/Sales Executive: Commission-based per sale
  - Community Manager & Marketing lead: 40, 000 DZA
  - Accountant/Financial Expert: Project-basis
- **Marketing & Community Outreach:** Digital campaign costs and community trust-building events.

REVENUE STREAM

- Subscription fee paid by institutions for our services.
- Shared revenue generated from selling aggregated, high-purity sorted recyclables (plastics, cardboard, metal) directly to local recycling plants and industrial buyers. The national recoverable waste market is valued at over 200 billion DZD, with Plastics (15-17%) and Paper/Cardboard (8-10%) being the most abundant and profitable fractions in municipal solid waste.
- Our institutional clients who buy our smartbins receive a percentage of our sale (20% of the raw material value returned as a rebate on their subscription), incentivizing them to adopt our system over traditional dumpsters.

Figure 4: SYMBIOSE BMC Table

Conclusion.

This thesis addressed the urgent waste management crisis in Tlemcen, Algeria, where a 5–7% recycling rate and the absence of locally representative data prevented effective circular economy implementation. Through four interconnected chapters, the work established that Algeria's linear waste model violates both ecological boundaries and social foundations, surveyed the deep learning architectures necessary for intelligent waste classification, and demonstrated that Western-trained models fail on Algerian waste due to fundamental domain gaps. The SYMBIOSE project contributed three concrete outcomes: a realistic 560-image dataset of Tlemcenian household waste, a fine-tuned YOLOv11m detection model achieving 52.4% mAP50 with actionable per-class diagnostics, and a theoretical smart bin prototype integrating solar power, automated sorting, and biophilic design. The accompanying business model demonstrated economic viability through SaaS subscriptions and premium recyclables sales. While dataset scale and model performance remain below industrial thresholds, this work lays the essential foundation : *local data, local expertise, and locally grounded AI*, for transforming waste from a design flaw into a recoverable resource, repairing the broken symbiosis between humans and nature.

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Abstract

This thesis addresses the urgent problem of household waste management in Tlemcen, where unsorted waste, low source-separation awareness, and the absence of locally representative data limit effective recycling and circular economy initiatives. The study investigates whether artificial intelligence can support waste sorting at source through a smart bin system adapted to Algerian conditions. To this end, a locally relevant waste image dataset was created and augmented, and a pre-trained YOLO model was fine-tuned and evaluated on this data. The results show that models trained on Western waste datasets perform poorly when applied to local waste, confirming the need for domain-specific data and adaptation. The thesis contributes a foundational dataset for Algerian household waste, a fine-tuned detection model, and a theoretical basis for deploying smart bin technology in Tlemcen. Overall, the work demonstrates that locally grounded AI systems can support better waste sorting, improve material recovery, and strengthen circular economy strategies in Algeria.

Keywords : Waste management, Artificial Intelligence, YOLO, Smart bin, Source separation, Dataset, Circular economy, Algeria, Tlemcen, Recycling.

Résumé

Cette thèse aborde le problème urgent de la gestion des déchets ménagers à Tlemcen, où les déchets non triés, le faible niveau de sensibilisation au tri à la source et l'absence de données localement représentatives limitent les initiatives de recyclage et d'économie circulaire. L'étude examine si l'intelligence artificielle peut soutenir le tri des déchets à la source grâce à un système de poubelle intelligente adapté aux conditions algériennes. À cette fin, un ensemble de données d'images de déchets pertinents au niveau local a été créé et augmenté, et un modèle YOLO pré-entraîné a été affiné (fine-tuned) et évalué sur ces données. Les résultats montrent que les modèles entraînés sur des ensembles de données de déchets occidentaux sont peu performants lorsqu'ils sont appliqués aux déchets locaux, confirmant ainsi le besoin de données et d'une adaptation spécifiques au domaine. La thèse apporte comme contribution un ensemble de données de base pour les déchets ménagers algériens, un modèle de détection affiné et une base théorique pour le déploiement de la technologie des poubelles intelligentes à Tlemcen. Dans l'ensemble, ce travail démontre que des systèmes d'IA ancrés localement peuvent soutenir un meilleur tri des déchets, améliorer la valorisation des matériaux et renforcer les stratégies d'économie circulaire en Algérie.

Mots-clés : Gestion des déchets, Intelligence artificielle, YOLO, Poubelle intelligente, Tri à la source, Ensemble de données (Dataset), Économie circulaire, Algérie, Tlemcen, Recyclage.

ملخص

تتناول هذه الأطروحة المشكلة الملحّة المتعلقة بإدارة النفايات المنزلية في تلمسان، حيث تؤدي النفايات غير المفرزة، ونقص الوعي بالفرز من المصدر، وغياب البيانات الممثِلة محليًا إلى الحد من مبادرات إعادة التدوير والاقتصاد الدائري. تبحث الدراسة في مدى قدرة الذكاء الاصطناعي على دعم فرز النفايات من المصدر من خلال نظام حاويات ذكية يتكيف مع الظروف الجزائرية. وتحقيقًا لهذه الغاية، تم إنشاء وتوسيع قاعدة بيانات صور للنفايات ذات صلة بالسياق المحلي، كما تم ضبط وتقييم نموذج YOLO مدرب مسبقًا بناءً على هذه البيانات. تُظهر النتائج أن النماذج المدربة على قواعد بيانات النفايات الغربية تعطي أداءً ضعيفًا عند تطبيقها على النفايات المحلية، مما يؤكد الحاجة إلى بيانات خاصة بالمنطقة وتكييفها معها. تساهم هذه الأطروحة في توفير قاعدة بيانات أساسية للنفايات المنزلية الجزائرية، ونموذج كشف مضبوط بدقة، وأساس نظري لنشر تكنولوجيا الحاويات الذكية في تلمسان. وبشكل عام، يوضح هذا العمل أن أنظمة الذكاء الاصطناعي ذات الجذور المحلية يمكنها دعم فرز النفايات بشكل أفضل، وتحسين استرداد المواد، وتعزيز استراتيجيات الاقتصاد الدائري في الجزائر.

الكلمات المفتاحية: إدارة النفايات، الذكاء الاصطناعي، YOLO، الحاوية الذكية، الفرز من المصدر، قاعدة بيانات، الاقتصاد الدائري، الجزائر، تلمسان، إعادة التدوير.