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SmartEpiStock: An AI-Driven Solution for Warehouse Monitoring

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Dedications

To my dear parents,
For your unconditional love, silent sacrifices, and endless support. You are my strength, my safe haven, and my greatest blessing. This work is a reflection of your dedication and belief in me.

To my beloved sisters, Maha and Touka,
Thank you for your *constant presence*, *comforting words*, and *encouragement*.
You are more than sisters — you are my *lifelong companions* and *pillars of support*.

To my dearest friends,
For the *shared laughter*, *meaningful conversations*, and *support* through every challenge.
Thank you for *believing in me*, even when I doubted myself.

To all of you —
I dedicate this work with *deep gratitude* and *all my love*.

Résumé

Ce mémoire présente SmartEpiStock, une solution intelligente de surveillance des silos à grains reposant sur l'intégration de trois technologies majeures : l'Internet des Objets (IoT), le Deep Learning et les ontologies. Le système développé vise à améliorer la conservation du blé en surveillant en temps réel les conditions de stockage (température, humidité, CO, etc.), en détectant automatiquement les anomalies à l'aide d'un modèle MobileNetV3 entraîné sur des images de grains, et en inférant des risques à partir de règles logiques intégrées à une ontologie sémantique. Une application mobile conviviale permet de visualiser les alertes et l'état du silo, renforçant ainsi la capacité des agriculteurs à intervenir rapidement. L'approche proposée répond aux limites des méthodes traditionnelles de stockage, en combinant perception, analyse et raisonnement dans un système intelligent, autonome et adaptable.

Mots-clés: Agriculture de précision, Deep learning,IoT, MobileNetV3, Ontologie, Raisonnement sémantique, Silos à grains, Stockage intelligent, Surveillance temps réel.

Abstract

This dissertation introduces **SmartEpiStock**, an innovative solution for grain silo monitoring based on the integration of three key technologies: the Internet of Things (IoT), Deep Learning, and ontologies. The system is designed to optimize grain preservation by monitoring storage conditions in real time such as temperature, humidity, and CO, automatically detecting anomalies using a MobileNetV3 model trained on grain images, and assessing risks through logical rules embedded in a semantic ontology. An intuitive mobile application enables users to view alerts and silo status, thereby improving farmers' responsiveness. The proposed approach overcomes the limitations of traditional storage methods by combining perception, analysis, and reasoning into a smart, autonomous, and scalable system.

Keywords: Deep learning, Grain silos, IoT, MobileNetV3, Ontology, Precision agriculture, rReal-time monitoring, Semantic reasoning, Smart storage .

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Introduction

General Context

Wheat is one of the world's most essential food crops, playing a critical role in global food security and the economies of many countries [1]. After harvest, the safe and effective storage of wheat grains is vital to maintaining quality, preventing economic losses, and ensuring year-round availability [1]. However, storage conditions are vulnerable to numerous external factors such as temperature, humidity, air circulation, pest infestations, and microbial activity. If not properly controlled, these factors can rapidly degrade grain quality or even lead to total spoilage [2].

In the context of digital transformation, agriculture is undergoing a paradigm shift toward what is commonly known as *smart agriculture*. This new approach leverages emerging technologies—such as the Internet of Things (IoT), artificial intelligence (AI), and knowledge-based systems to enable real-time monitoring, intelligent decision-making, and dynamic control of storage environments [3]. Within this framework, the present work proposes the development of an intelligent wheat grain storage system that integrates multiple technologies to ensure optimal preservation and proactive risk management.

Problem Statement

The rapid growth of heterogeneous data sources and the rising demand for automation in agricultural management highlight the limitations of traditional grain storage systems. These legacy systems are often rigid, poorly scalable, and incapable of adapting to real-time environmental changes. Moreover, they typically lack the capacity to fully exploit the rich and diverse data generated by modern sensing technologies.

On one hand, IoT technologies provide the infrastructure for continuous, large-scale data collection from the physical environment. However, this raw sensor data requires intelligent processing to yield actionable insights. On the other hand, deep learning techniques—particularly convolutional neural networks (CNNs)—have demonstrated strong performance in analyzing complex data types like images, but often operate as opaque "black boxes" with limited interpretability and no built-in understanding of domain knowledge.

Semantic technologies, particularly ontologies, address this shortcoming by providing a formal and interpretable framework for representing domain knowledge and supporting logical reasoning. However, ontologies alone are not equipped to perform perceptual analysis of unstructured data such as images or real-time sensor streams.

Consequently, the core challenge addressed by this research is the design of an integrated intelligent system capable of:

- Collecting and aggregating real-time contextual data via IoT sensors;
- Automatically analyzing this data using deep learning models;

[1] https://www.fao.org/publications/fao-flagship-publications/the-state-of-food-and-agriculture/2021/en

- Reasoning over the extracted knowledge using an agricultural ontology enhanced with logical inference rules.

This hybrid approach aims to unify perception, semantic understanding, and reasoning within a scalable and autonomous architecture, thereby overcoming the limitations of conventional storage monitoring solutions.

Objectives

The primary objective of this dissertation is to design and implement an intelligent wheat grain storage system capable of:

- Automatically detecting environmental conditions and grain characteristics that may compromise storage quality;
- Identifying damaged and infected grains through image-based classification;
- Generating timely alerts and supporting preventive interventions.

To achieve this, the project sets out the following specific objectives:

- Train a deep learning model (MobileNetV3) to classify wheat grains based on grain images;
- Construct an agricultural ontology enriched with Semantic Web Rule Language (SWRL) rules to infer critical storage risks;
- Implement a user-friendly mobile application to visualize alerts, monitor system status, and facilitate user interaction.

Contribution

This work makes several scientific and technical contributions to the field of intelligent agricultural systems:

- Design of a real-time data acquisition system incorporating temperature, humidity, and motion sensors, along with imaging devices to capture grain conditions;
- Implementation and training of a lightweight, efficient MobileNetV3 model for classifying wheat grains into health categories;
- Development of an agricultural ontology integrated with SWRL rules to enable inference of high-risk storage scenarios based on sensor and image data;
- Creation of a mobile application that provides real-time monitoring, interactive feedback, and alerts for proactive storage management.

Disertation structure

This dissertation is organized into two main chapters, each addressing a key component of the proposed intelligent system for wheat grain storage monitoring, followed by a general conclusion.

- **Chapter 1: State of the Art — Synergy of Technologies for Wheat Grain Storage Monitoring**
  This chapter presents a comprehensive review of the existing literature and technological approaches relevant to grain storage. It explores the challenges associated with post-harvest wheat preservation and examines the role of emerging technologies such as the Internet of Things (IoT), deep learning, and semantic ontologies. Particular emphasis is placed on how these technologies can be synergistically combined to address the limitations of traditional storage systems and to enable intelligent, adaptive monitoring frameworks.

- **Chapter 2: Methods and Materials**
  This chapter details the methodological framework adopted for the development of the intelligent storage system. It describes the architecture of the proposed solution, including the IoT-based data acquisition system, the image classification model based on MobileNetV3, and the design of the agricultural ontology with SWRL-based reasoning. It also outlines the datasets used, the experimental setup, the tools and platforms employed, and the implementation of the mobile application for system interaction and alert visualization.

- **Conclusion**
  The dissertation concludes by summarizing the key findings, highlighting the contributions of the proposed system, and discussing its limitations and potential directions for future research.

Chapter 1

State of the Art: Synergy of Technologies for Wheat Grain Storage Monitoring

1.1 Introduction

Ensuring the safe and long-term storage of wheat grain is a critical component of food security and supply chain stability. However, post-harvest grain management continues to face significant challenges due to environmental variability, biological threats, and the limitations of traditional monitoring systems. As wheat remains a staple food for a large portion of the global population, maintaining its quality during storage is a priority for both producers and policymakers.

This chapter provides a comprehensive overview of the key factors affecting wheat grain storage and introduces modern technological solutions that aim to address these issues. It begins with a discussion of the fundamentals and challenges associated with wheat storage, followed by an analysis of the major causes of storage losses, including biotic and abiotic factors. The chapter then explores how storage conditions such as temperature, humidity, and airflow influence the physical and nutritional quality of wheat over time.

To respond to these challenges, the chapter presents a set of enabling technologies that form the foundation of intelligent storage systems. It examines the Internet of Things as a platform for real-time, context-aware monitoring of storage environments through distributed sensors. It then introduces deep learning techniques, particularly convolutional neural networks (CNNs), which provide powerful capabilities for image-based grain quality assessment and predictive modeling. Finally, the chapter discusses the role of ontologies in formally representing domain knowledge, enabling semantic reasoning, and supporting decision-making processes.

1.2 Wheat Grain Storage: Fundamentals and Challenges

1.2.1 Traditional Storage Techniques

Since prehistoric times, various storage systems and techniques have been developed to prolong the availability of seasonal food resources beyond their natural harvesting period [4]. In Africa, three major types of storage systems exist, each with distinct structural characteristics: traditional or local storage, which includes local cribs and rhombus structures, platforms, open fields, rooftops, and fireplaces; improved or semi-modern storage, such as ventilated cribs, enhanced rhombus structures, and brick bins; and modern centralized storage used commercially, involving silos and warehouses.

The first two storage types are the most widespread, as agriculture is predominantly practiced by subsistence farmers [5]. Whether traditional or modern, several methods are used for storing cereals, but five are considered particularly important due to their effectiveness and frequency of use. These key methods include:**bulk storage, storage in bags, storage in metal or concrete silos,traditional granaries and hermetic storage**,Each of these methods offers specific advantages and faces particular limitations during the storage period [6].

1.2.1.1 Underground Storage Practices(Matmour System)

Underground storage was a traditional and essential practice for the long-term preservation of surplus cereals in farming communities. Grain could be stored for several years in these underground pits, which provided a cool and often airtight environment[7]. However, grain located near the surface and along the edges was frequently prone to mould. These pits varied in capacity and could hold more than 1,000 kg of grain. They were typically located either inside or outside houses. The pit opening was usually round and large enough for a person to enter, with a bell-shaped cross-section (Figure 1.1). The top was sealed with a flat stone combined with mud or cow dung to create an airtight barrier that prevented water infiltration and pest intrusion. When the pits were dug into the soil, the ground needed to be compact and hard to minimize water seepage [4]. This traditional storage method, known as Matmours silos, still exists in Algeria.

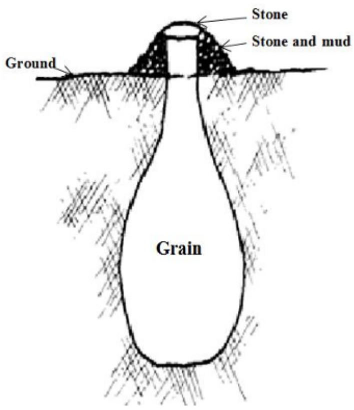

Figure 1.1: Sectional view of an underground silo (Matmour) [8]

Figure 1.2: Appearance of a 'Matmour' [9]

1.2.1.2 Storage in warehouse

A warehouse is designed to store and physically protect grains, whether in bulk or in bags. It can also accommodate equipment and materials necessary for packaging, handling, and pest control. When choosing a warehouse location, several factors should be taken into account, including topography, soil type, ease of access, orientation, and proximity to residential areas [6].

Bulk storage: Grain can be effectively stored in both vertical and horizontal warehouses (Figure 1.3). In this method, the surface of bulk-stored cereals such as wheat, barley, rye, oat, corn, chickpea, and lentil must be properly leveled. This technique allows for a greater volume of grain to be stored per unit area, facilitates easier sampling and monitoring, reduces labor costs, and saves time [6]. Further advancements have been made in bulk storage systems through the integration of pest monitoring technologies (such as acoustic detection) and the automation of key processes including aeration, grain cooling, and pest control [10].

Figure 1.3: Bulk Storage
[1]

Storage in bag: For extended storage periods, certain types of grains like wheat are not suitable for bulk storage; therefore, they are stored in bags (Figure 1.4) to maintain quality. The moisture level in the grain is a crucial element of this method. An increase in moisture content leads to a reduction in the number of bags in storage. This technique facilitates easy counting of the bags and sampling from each one, but managing the products becomes challenging since they are bagged. Additionally, the quantity of grains stored per unit area is lower compared to bulk storage methods. This approach is also costlier due to higher labor expenses and is more time-consuming, which increases the risk of rodent damage [11].

Figure 1.4: Bag storage
[2]

[1] https://pvc-hall.fr/bulk-storage-hall/

[2] http://www.knowledgebank.irri.org/step-by-step-production/postharvest/storage/grain-storage-systems/bag-storage

1.2.1.3 Storage in silo

Silos (Figure 1.5) represent an efficient method for grain storage. Bulk storage saves space and facilitates mechanical handling, thereby reducing packaging and processing costs. Air recycling inside silos, through aeration, is essential to prevent increases in grain temperature a key aspect of silo management. There is a wide variety of silos of different sizes for bulk grain storage. These structures can be made of concrete, bricks, or assembled sheet metal [12].

Figure 1.5: Storage in silo
[3]

1.2.2 Modern and Innovative Storage Solutions

Recent advancements in grain storage technologies have led to the development of improved systems such as aeration, cold storage and hermetic storage particularly in industrialized nations [13].

1.2.2.1 Grain Aeration Techniques

Aeration is one of the most commonly used methods for preserving stored grain. It involves the forced circulation of surrounding air either natural or conditioned through a bulk of grain to enhance its storability. This technique is particularly effective for reducing grain temperature and is typically carried out using fans and mechanical systems. Designed primarily for environments with low humidity, forced aeration plays a crucial and efficient role in commercial grain preservation [2].

1.2.2.2 Refrigerated storage

One of the main goals of refrigerated aeration in subtropical climates is to lower the grain temperature below 18°C when ambient temperatures are too high to effectively suppress insect activity. In this method, cooled ambient air is circulated through the bulk grain using standard aeration systems. When combined with air-drying techniques, this method offers valuable insight into the viability of aeration for ensuring safe commercial storage in tropical environments [2] [14].

[3] http://www.silosupplier.com/grain-silo-advantages-benefits/
[4] https://pradosilos.com/aeration-systems/
[5] https://siila.com.br/news/refrigerated-warehouses-know-how-they-work/373/lang/en

Figure 1.6: Modern Silo with Aeration Systems
4

Figure 1.7: Refrigerated storage
5

1.2.2.3 Hermetic storage

The foundation of hermetic storage (Figure 1.8) is bio-generated environments. The production of low-oxygen and An interstitial atmosphere enriched in carbon dioxide is a outcome of the aerobic organisms' respiration residing inside the product [15]. The process allows insects and other living things that breathe in the grain or the grain itself to produce the altered environment by decreasing O2 and elevating CO2 levels via metabolism of the respiratory system. Breathing exercises the living things produces an atmosphere. comprising roughly 20% CO2 and 1% to 2% O2. Success of insect control because of the hermetic storage treatment is similar to that of traditional fumigants.(more than 99.9% fatality), and losses brought on by insect activity little. An atmosphere with low O2 and high CO2 kills pests such as insects and mites, and stops aerobic fungi from expanding [13].

1.2.3 Major Causes of Storage Losses

During storage, wheat grains are subject to various types of losses that can compromise their quality and nutritional value. These losses are mainly caused by biological agents such as insects, mites, and rodents, whose activity leads to both physical damage and microbial contamination of the grains.

[6] https://www.researchgate.net/figure/Different-kinds-of-hermetic-storage-containers-available-for-use-by-small-holder-farmers_fig6_344329525

Figure 1.8: Different kinds of hermetic storage containers available for use by small holder farmers

[6]

1.2.3.1 Insect Infestation

Insects are among the first and most significant threats to grain quality during storage. They consume the grain, contaminate it, and spread microorganisms [10]. It is critical to monitor and diagnose stored-grain insect infestations early in order to take timely and effective pest control measures to protect stored grains[16]. Losses caused by insect infestations are typically assessed in terms of weight reduction. However, the impact goes beyond that, as insect activity also affects the nutritional composition of the grain, with certain nutrients being more severely degraded than others [17]. More than 100 insect species are known to infest stored grains, the majority being beetles, followed by moths and a group of primitive insects called psocids [10].

Figure 1.9: Psocids

[7]

1.2.3.2 Mites

Throughout the processing and storage stages, mites represent significant pests of wheat and other cereals. Due to their microscopic size, they are difficult to detect with the naked eye and can cause considerable economic losses if not properly managed. Mites are responsible for both qualitative and quantitative degradation of stored grains. They primarily target

[7]https://bugspray.com/psocids-questions-about-how-to-treat
[8]https://www.bugfreegrains.com/blog/grain-insects/stored-grain-insect-identification

Figure 1.10: Beetles
8

and consume the germ, significantly damaging its contents, while also feeding though to a lesser extent on other grain components [18] [19].

Figure 1.11: Mites
9

10

1.2.3.3 Rodents

Rats and mice can cause significant damage to both standing crops and stored products. This damage can occur in several ways [20]:

- by consuming part of the stored products
- by contaminating food with their droppings
- by damaging buildings, storage containers, and packaging materials
- moreover, they are carriers of diseases that pose serious risks to human health

1.2.3.4 Micro-organisms

Microorganisms from the field and during storage such as fungi, yeasts, and bacteria play a major role in the deterioration of grains during storage. Yeasts tend to dominate in sealed silos under low oxygen conditions and when grain moisture is high. Bacteria thrive in grains when water activity exceeds 0.9%, leading to grain degradation. Sources of contamination by both field and storage fungi include soil and decomposing plant debris, but they may also originate from harvesting and grain-handling equipment. Key field fungi that infect grains before threshing or while still on the farm include species such as Alternaria, Cladosporium, Fusarium, and Drechsclora. These fungi target grains with moisture content over 20%.

[10] https://www.mamawax.fr/blog/les-mites-alimentaires-qui-sont-elleset-comment-sen-debarrasser--n73

However, their harmful effects diminish as the grain dries during storage at that point, the fungi either die or persist as dormant mycelium within the grain [10].

1.2.4 Influence of Storage Conditions on Wheat Quality

1.2.4.1 Moisture

Moisture plays a critical role in managing grain infestations. Insects that inhabit stored grains and their by-products rely heavily on available moisture for survival. Typically, when the grain moisture content is 8% or lower, insect activity is significantly limited. Moisture is also a key factor in ensuring the safe storage of cereals and their derivatives with respect to microbial contamination, especially by certain fungal species. Fungal growth is inhibited under low moisture conditions, but begins to occur when the moisture content reaches approximately 13% or slightly higher [21].

1.2.4.2 Temperature

During storage, wheat temperature tends to rise, primarily due to insect infestation. These insects not only feed on the grains for energy and growth, but they also undergo respiration, releasing heat into the surrounding environment [22].

The effects of temperature on pests are well established. Between 30 and 40 °C, molds and insects actively proliferate, which accelerates the deterioration of the grain. From 40 °C up to 55 °C, damage is observed at the seed level itself, compromising their viability. When the temperature is between 25 and 30 °C, the biological activity of molds and insects remains significant. Between 20 and 25 °C, mold development becomes more limited. At 18 to 20 °C, the development of young insects stops. Finally, when the temperature drops below 15 °C, reproduction of most insects ceases, and molds also stop developing. Thus, Maintain grain temperatures below 23 °C in summer and below 15 °C in winter to prevent pest activity and preserve grain quality during storage [11].

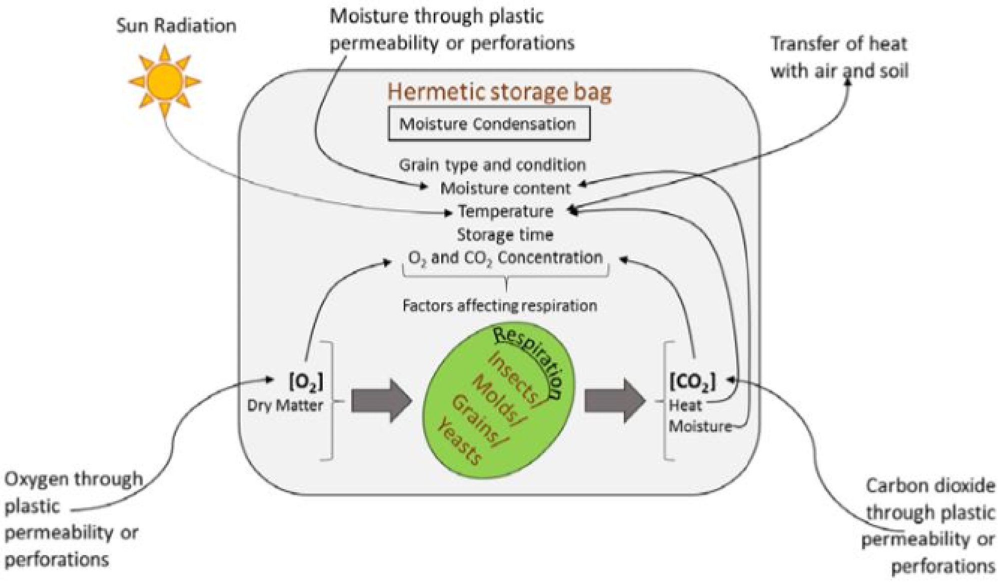

Figure 1.12: Factors affecting the grain and microorganism respiration in the hermetic storage [23]

[11] https://storedgrain.com.au/tag/pest-control-guide/

1.2.4.3 Biochemical changes

Grain moisture content plays a critical role in these biochemical processes. When the moisture content exceeds 18%, molds and insects become highly active, leading to rapid grain deterioration. Between 13% and 18%, biological activity remains significant and continues to impact wheat quality. A moisture range between 10% and 13% limits mold development, while at 9%, the development of young insects comes to a halt. Finally, when moisture content drops below 8%, most insects stop reproducing and molds cease to grow. Therefore, maintaining grain moisture below 13%, and ideally under 8% for long-term storage, is essential to slow down biochemical degradation and preserve grain quality [12].

1.2.5 Current Challenges

Traditional wheat storage methods, including underground pits (Matmours), jute bags, and even modern silos, present significant limitations in ensuring long-term grain quality and safety. These approaches often rely on manual inspections and lack the ability to detect early signs of deterioration such as mold growth, insect infestation, and moisture accumulation. Environmental conditions—especially temperature and humidity—are rarely monitored in real time, leading to delayed interventions and substantial post-harvest losses. Moreover, traditional systems are reactive, labor-intensive, and unable to adapt to dynamic storage conditions. These shortcomings are particularly critical in hot and humid climates, where biological activity accelerates spoilage.

To address these persistent challenges, Internet of Things (IoT) technologies offer a transformative solution by enabling real-time environmental monitoring.

1.3 Existing IoT-Powered Systems for Intelligent Grain Storage

The Internet of Things (IoT) refers to a network of interconnected physical or virtual "things" (sensors, devices, machines) embedded with processing capabilities, communication interfaces, and unique identifiers. These components autonomously collect, transmit, and act on data via the internet without human intervention. In agriculture, IoT enables real-time visibility into environments (e.g., grain silos) and processes (e.g., aeration control) previously reliant on manual oversight [24].

A comprehensive review of IoT-based monitoring systems for grain storage was conducted in previous master work under the same academic supervision [25]. That review systematically analyzed scientific publications between 2018 and 2023 to identify sensor technologies and architectures deployed in intelligent grain warehouse management. Key studies addressed diverse challenges such as environmental monitoring, grain theft prevention, and inventory tracking. The systems described typically integrate temperature and humidity sensors, gas detectors, vibration and motion sensors, RFID technologies, and microcontrollers such as Arduino, Raspberry Pi, or NodeMCU. Some approaches further incorporate machine learning tools and cloud-based platforms for real-time visualization and forecasting.

The insights gained from that review form the foundation for the present study, which aims to build upon these findings by proposing an enhanced, multi-technology solution tailored for efficient and intelligent wheat grain storage.

[12] https://storedgrain.com.au/tag/pest-control-guide/

1.3.1 Challenges with Existing Systems

The problem with existing IoT-systems is that sensor networks generate fragmented, heterogeneous data streams [26]—temperature, humidity, CO_2, and images—in incompatible formats, creating silos that prevent holistic analysis. Rule-based threshold alerts fail to capture nonlinear interactions between variables (e.g., humidity spikes accelerating mold growth only above 25°C), leading to reactive, post-failure interventions.

Meanwhile, visual inspection struggles with grain diversity, dust occlusion, and lighting variations, causing unreliable defect detection. Raw sensor values (e.g., "500ppm CO") lack actionable context without domain knowledge—such as grain type or storage duration—leaving operators blind to emerging risks.

These systems also cannot scale expert rules to cover dynamic threats. AI models can overcome these gaps [27]. Ontologies then can inject domain intelligence, semantically unifying data into knowledge graphs that infer causality and prescribe actions [26].

Through this fusion storage systems can evolve from reactive monitoring to predictive, adaptive intelligence—transforming raw data into decisions that preempt loss.

1.4 Artificial Intelligence for Agricultural domain

Artificial Intelligence is commonly understood as a field encompassing science, engineering, and technology aimed at replicating intelligent behavior by mimicking human abilities such as reasoning, perception, and response [28]. Moreover, AI is defined by a system's capacity to accurately analyze external inputs, learn from them, and apply that knowledge to accomplish designated objectives with adaptive flexibility [29]. It is also considered a form of machine-based information processing that imitates human cognitive functions [30]. Ultimately, the overarching aim of AI is to build autonomous systems capable of perception, learning, decision-making, and interaction, thereby fostering innovation across sectors like healthcare, finance, transportation, and beyond [31]. Furthermore, AI encompasses various subfields such as machine learning, deep learning, natural language processing, and computer vision.

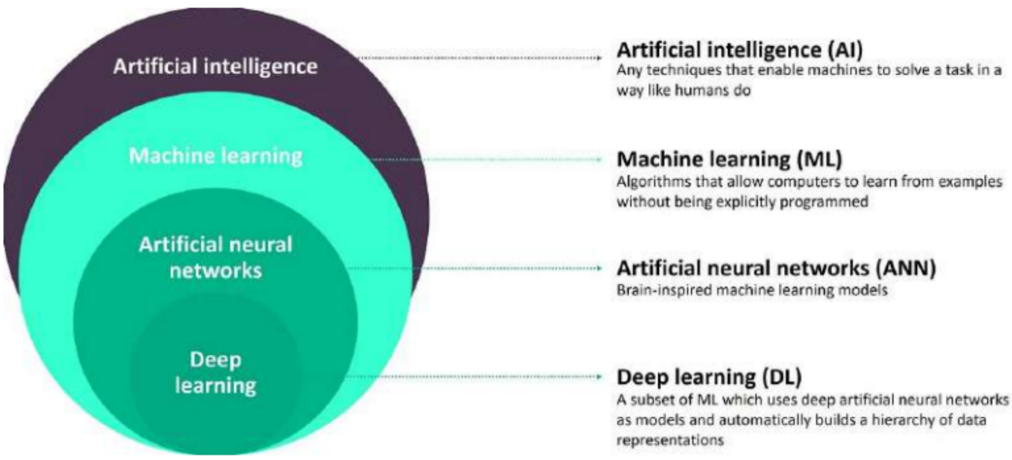

Figure 1.13: Different subdomain of AI [32]

1.4.1 Theoretical Foundations

1.4.1.1 Machine Learning

"Machine Learning is a field of study that gives computers the ability to learn without explicitly being programmed.," (Arthur Samuel, [33]).

In broad terms, machine learning represents a modern application of artificial intelligence (AI) that enables computers to independently learn from experiences and enhance their performance without needing specific programming. The idea is to grant machines access to data, allowing them to learn autonomously. This relies on the machines' capability to understand the data's structure and convert it into models that can be understood and utilized by humans [34].

Machine learning encompasses several learning paradigms, including Supervised Learning, Unsupervised Learning, Semi-Supervised Learning, and Reinforcement Learning. There are several popular machine learning algorithms, including Support Vector Machine (SVM) [35], K-Nearest Neighbor (KNN) [36], Decision Tree (DT), Random Forest (RF) [37], K-means [38], Fuzzy C-Means (FCM) [39], Naïve Bayes (NB), Logistic Regression (LR) [40], and the Gaussian Mixture Model (GMM).

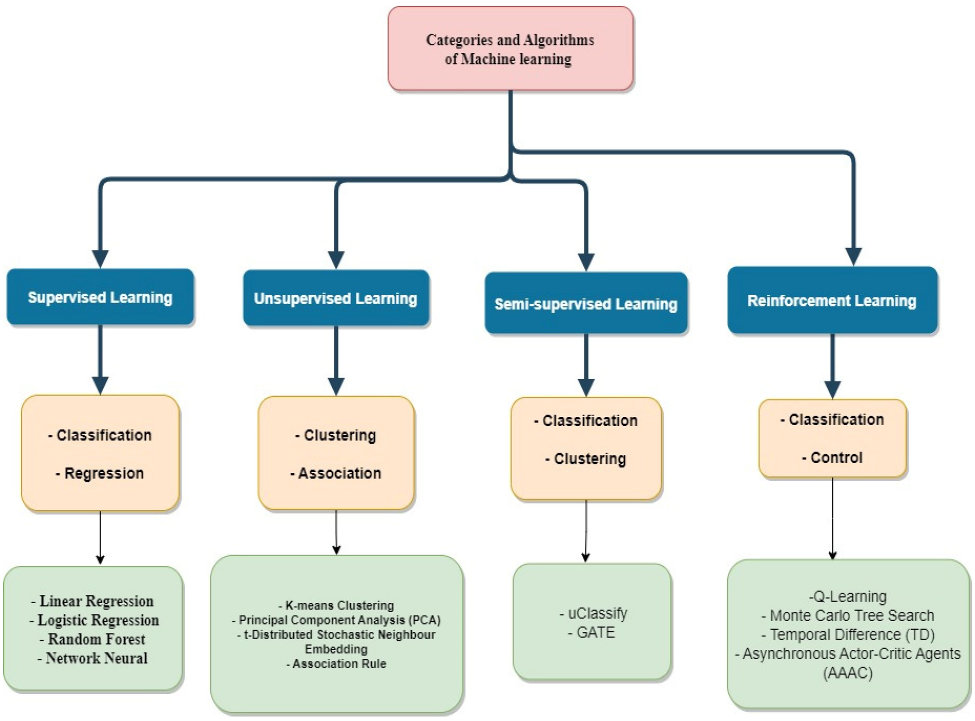

Figure 1.14: Different machine learning categories and algorithms [41]

1.4.1.2 Deep Learning

Deep learning represents a type of machine learning that allows computers to gain insights from experiences and comprehend the world through a structured set of concepts. Since the computer accumulates knowledge through experience, there is no requirement for a human operator to explicitly outline all the information necessary for the computer [42].

Deep learning relies on artificial neural networks that consist of numerous layers (thus the term "deep") which allow for the automatic identification of features from unprocessed data. It includes various subfields and specific architectures, including Convolutional Neural Networks (CNNs) for handling images, Recurrent Neural Networks (RNNs) for sequential information like language or time series, and Generative Adversarial Networks (GANs) for producing new data. Each of these subfields targets distinct types of tasks and data forms, driving progress in fields like computer vision.

1. Artificial Neural Networks (ANNs)
   ANNs are computational processing systems of which are heavily inspired by way biological nervous systems (such as the human brain) operate. ANNs are mainly comprised of a high number of interconnected computational nodes (referred to as neurons), of which work entwine in a distributed fashion to collectively learn from the input in order to optimise its final output [43].

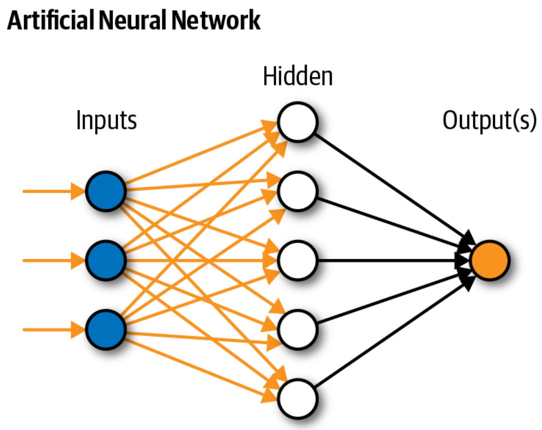

Figure 1.15: The architecture of ANN [44]

2. Deep Neural Networks (DNNs)
   A Deep Neural Network (DNN), or deep learning model, refers to an artificial neural network (ANN) composed of multiple hidden layers [45]. These additional layers enable the network to learn increasingly abstract and complex data representations [46]. Deep learning models have shown remarkable performance when applied to large-scale datasets, achieving significant breakthroughs in areas such as speech recognition, computer vision, pattern recognition, recommendation systems, and natural language processing [47].

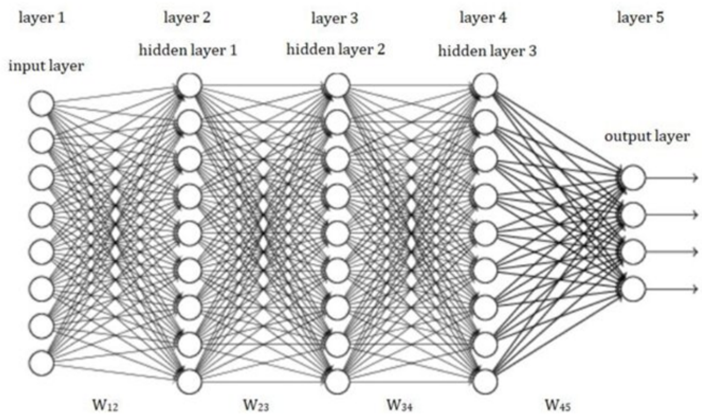

Figure 1.16: A structure of a DNN [48]

3. Convolutional Neural Network (CNN)
   Convolutional Neural Networks (CNNs) [49] are a class of feedforward artificial neural networks particularly well-suited for extracting complex and hierarchical features.

They are widely used in image and video analysis tasks due to their ability to maintain spatial relationships between pixels. Unlike traditional ANNs, which treat individual pixels independently and thus lose spatial structure [50], [51], [46], CNNs process local pixel regions, or patches, collectively. Each patch is mapped to specific nodes in the next layer, preserving the relative position of visual features.

A typical CNN architecture consists of several deep layers. Early layers are responsible for detecting low-level features such as edges and corners, while deeper layers extract more abstract and complex patterns for object recognition. The key components of a CNN include convolutional layers, pooling layers, and fully connected layers. Notable CNN architectures include MobileNet [52], DenseNet [53], ResNet [54], and GoogleNet [55].

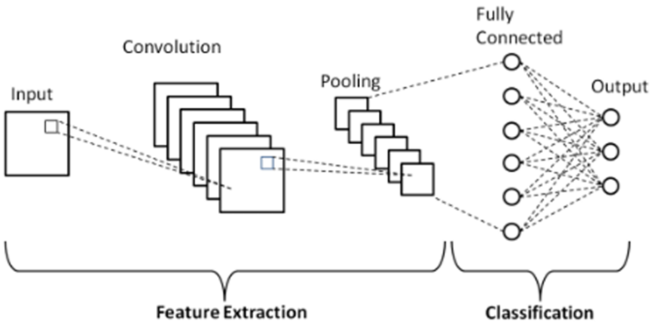

Figure 1.17: A structure of a CNN [56]

4. Generative Adversarial Networks (GANs)
   GANs are a type of deep learning model consisting of two neural networks: a generator and a discriminator. The generator learns to produce synthetic data that closely resembles real data, while the discriminator learns to distinguish between real and generated data. Through an adversarial training process, both networks improve by competing with each other. This enables GANs to generate high-quality synthetic content, such as images, videos, or other data that can be difficult to distinguish from real-world examples [57].

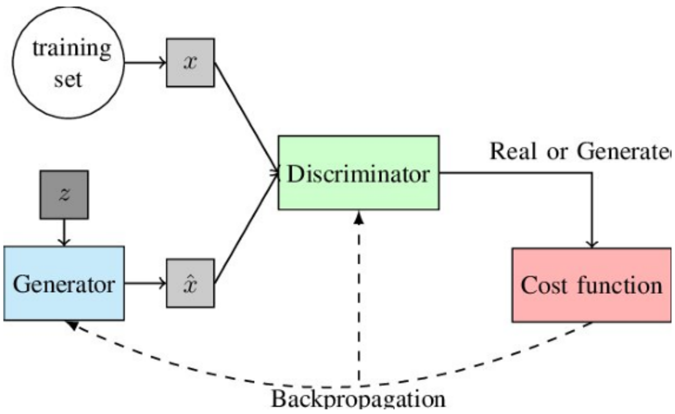

Figure 1.18: A structure of a GAN [56]

5. Autoencoders (AE)
   An Autoencoder (AE) is a type of feedforward artificial neural network designed for unsupervised learning tasks. Its main objective is to filter out irrelevant noise while preserving the most significant information from the input data [58]. The network

functions in two main phases: the encoding phase, where input data is compressed into a lower-dimensional representation, and the decoding phase, where it attempts to reconstruct the original input from this compressed form. AEs are particularly effective for anomaly detection, as they can identify unusual data points by measuring reconstruction errors, which are typically much higher for anomalies than for normal inputs [59]. Structurally, an AE is composed of three main components: the encoder, the latent code (or bottleneck), and the decoder

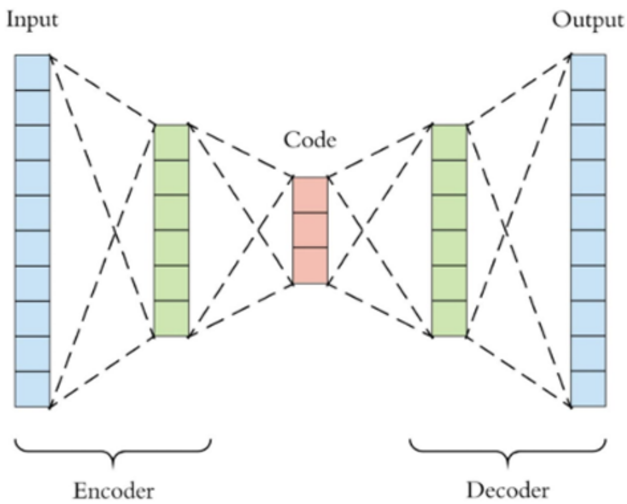

Figure 1.19: An AE structure [60]

6. Transformer

   A Transformer [61] is a type of artificial neural network designed to capture contextual relationships in sequential data through the use of a self-attention mechanism, which allows for efficient parallel processing [62]. Initially developed for natural language processing (NLP), Transformers are now widely applied across diverse domains where data can be represented as sequences, including computer vision, speech recognition, and more.

7. Long Short-Term Memory Networks (LSTM) Long Short-Term Memory (LSTM) networks [63] are a specialized type of Recurrent Neural Network (RNN) designed to capture long-term dependencies in sequential data through the use of memory cells. Their primary objective is to overcome the limitations of traditional RNNs, particularly the vanishing gradient problem, by enabling gradients to flow more effectively during training [64]. This vanishing gradient issue occurs when gradients become too small during backpropagation through time, impairing the model's ability to learn long-range patterns. LSTMs address this by incorporating memory cells and gating mechanisms that regulate the flow of information. Due to these capabilities, LSTMs have been widely applied in tasks such as time series forecasting, speech recognition, and natural language processing. As illustrated in Figure X, an LSTM unit typically consists of a memory cell, along with input, output, and forget gates.

1.4.2 Deep Learning Models in Agricultural Seed Classification Tasks

In this section, we focus on the application of deep learning techniques to grain classification. To conduct a comprehensive review, we performed a structured search using the query "Deep learning and grain quality classification" on the Mendeley database. This search initially

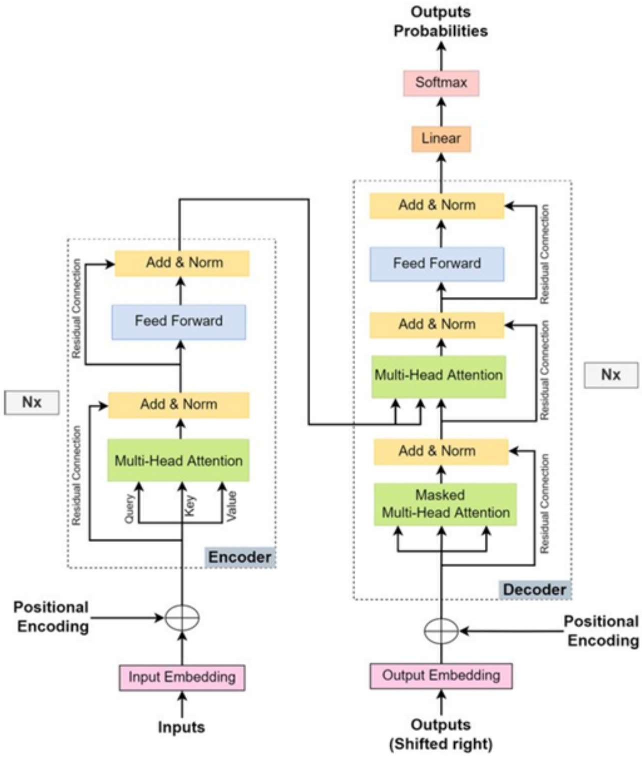

Figure 1.20: A transformer structure [62]

returned 3,126 papers. From this set, we filtered 2,286 articles published in scientific journals and conference proceedings. We then narrowed the selection to papers published between 2021 and 2024, resulting in 2,084 articles. To ensure accessibility and reproducibility, we prioritized open access publications, which reduced the number to 13 articles. After a thorough reading and critical evaluation of these documents, we identified 14 papers as highly relevant to our specific area of interest:

The authors in [66] focuse on automating the identification of wheat varieties, a crucial task for seed testing and certification. The researchers employed various Convolutional Neural Network (CNN) architectures, including DenseNet201, Inception V3, and MobileNet, leveraging transfer learning techniques. The dataset used consisted of 31,606 single-grain images representing four wheat varieties: Simeto, Vitron, ARZ, and HD, collected from different regions in Algeria. The results showed that the DenseNet201 model achieved the highest accuracy of 95.68%, followed closely by Inception V3 at 95.62% and MobileNet at 95.49%. These findings demonstrate the effectiveness of deep learning models in accurately classifying wheat varieties, highlighting their potential for use in seed testing and certification processes.

In this study [67], a deep learning-based approach was proposed for barley classification using pre-trained Convolutional Neural Networks (CNNs), specifically VGG-16, and transfer learning. The methodology focused on overcoming the challenge of having a relatively small number of samples by leveraging transfer learning from the large-scale ImageNet dataset. The VGG-16 architecture was chosen for its strong performance in image classification tasks, and the final layer was modified for the barley classification task. The model was tested with different classifiers, including Support Vector Machine (SVM) and softmax, to evaluate its effectiveness.

The article [68] addresses the challenge of visual inspection of grain quality typically a manual, slow, and error-prone process—by introducing GrainSet, a large annotated image database designed to support automated grain classification. GrainSet comprises over

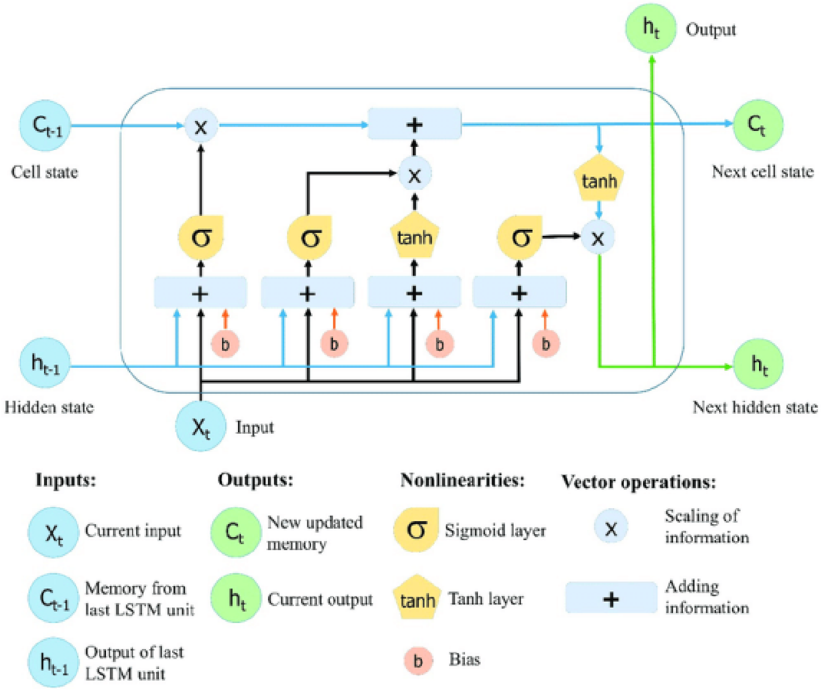

Figure 1.21: A structure of LSTM [65]

350,000 high-resolution images of individual kernels (wheat, maize, sorghum, rice), collected from more than 20 regions in 5 countries and labeled by experts based on morphological traits, weight, size, and various defect types (such as damaged, moldy, or broken grains). The deep learning model used in the study is based on ResNet-50, enhanced with a Squeeze-and-Excitation (SE) attention module, and trained to classify kernels into eight categories: normal, six types of defects, and impurities. The dataset is structured by grain type, and the model demonstrated excellent performance, achieving average F1-scores of 99.9% for wheat, 97.2% for maize, 96.8% for sorghum, and 94.1% for rice.

The article [69]introduces a highly effective and intelligent method for the automatic classification of rice varieties, called ARVDC-QIMFODL, which integrates a deep Convolutional Neural Network (CNN) with a Quantum-Inspired Moth Flame Optimizer (QIMFO). This approach addresses the challenge of distinguishing between rice varieties that are visually very similar by automating the identification process using image-based deep learning. The ARVDC (Advanced Rice Variety Detection CNN) is responsible for extracting discriminative visual features from grain images, while QIMFO dynamically optimizes the CNN's hyper-parameters such as learning rate, number of filters, and kernel size to enhance accuracy and model generalization. Additionally, the study evaluates a Long Short-Term Memory (LSTM) model, a type of Recurrent Neural Network (RNN), for comparison purposes. However, the LSTM underperforms compared to the CNN-based architecture, reaffirming the suitability of CNNs for image classification tasks. The dataset includes five rice varieties—Ipsala, Arborio, Basmati, Jasmine, and Karacadag—and is split into training and testing sets using a 70/30 ratio.

The work [70] addresses the challenge of automatically segmenting and classifying airborne pollen grains from scanning electron microscope (SEM) images, particularly in real-world environments where images often contain numerous impurities. The main problem lies in the lack of detailed pixel-level annotations, which makes fully supervised approaches expensive and impractical. To overcome this, the authors propose a weakly supervised collaborative learning framework that combines two deep learning modules: a segmentation module based on U-Net, trained using pseudo-masks generated through unsupervised methods, and a mask-guided classification module built on a DenseNet architecture enhanced with Grad-CAM to extract discriminative activation regions. These two modules are trained iteratively and cooperatively, allowing each to refine the predictions of the other. The dataset used consists of 1324 real SEM images of three pollen types (Cupressaceae, Fraxinus, Ginkgo), collected in Beijing, and labeled only at the image level (global labels) for supervision. Experimental results show a significant improvement over classical models (VGG, ResNet, MobileNet).

This article [71] addresses the problem of identifying and classifying peanut varieties, a crucial task for seed sorting, phenotype collection, and scientific breeding programs. The authors propose a method based on deep learning, specifically an improved version of the VGG16 model, in which the fully connected layers F6 and F7 were removed, a Conv6 convolutional layer was added, along with a Global Average Pooling (GAP) layer, Batch Normalization (BN) layers, and an Inception-style structure integrated into the Conv5 block. The model was trained on a dataset composed of 3,365 scanned images of 12 peanut varieties, which were segmented and labeled accordingly. The images were preprocessed (grayscale conversion, binarization, ROI extraction) and divided into training, validation, and test sets using an 8:1:1 ratio. The results show that the improved model achieved an average accuracy of 96.7% on the test set, compared to 87.8% for the standard VGG16.

In [72], the authors addressed the challenge of recognizing imperfect wheat grains, which are visually similar to perfect ones and difficult to classify using conventional image features. To improve classification performance, they proposed a deep learning approach combining Residual Networks (ResNet) with the Convolutional Block Attention Module (CBAM). The dataset consisted of RGB images (100×100 pixels) of six wheat grain categories, with 3000 training images per class after augmentation.

The authors of [73] addressed the problem of automatically identifying multiple rice grain varieties, which is essential for quality control in agriculture and difficult to achieve accurately with traditional methods. They proposed a deep learning-based two-stage framework combining DarkNet19 and SqueezeNet architectures to improve classification performance. The system processes RGB images of five rice grain types (Khazar, Gharib, Ghasrdashti, Gerdeh, and Mohammadi), using 75,000 labeled images for training and testing. Features extracted from both CNN models were fused and optimized using the Butterfly Optimization Algorithm (BOA) to select the most relevant information. The best results were achieved after feature fusion and selection, reaching 100% classification accuracy using a cubic SVM, demonstrating the effectiveness of combining lightweight CNN models with optimization techniques for precise and efficient multiclass grain identification.

The article [74] addresses the research problem of automating the classification of five rice seed varieties grown in Turkey, traditionally a manual, time-consuming, and error-prone process. It applies Deep Learning techniques, specifically computer vision, to improve accuracy and efficiency. Four Convolutional Neural Network (CNN) models were used: VGG, ResNet, EfficientNet, and a custom-designed CNN. The data type consists of 6,833 high-resolution images of rice seeds captured with a digital microscope. The results show that the VGG model achieved the highest accuracy at 97%, followed closely by the custom CNN, demonstrating the effectiveness of deep learning models in agricultural seed classification tasks.

This study [75] addresses the research problem of accurately detecting and classifying closely related grain storage pests Tribolium and Sitophilus species—in real wheat storage conditions, where manual identification is difficult and hazardous. Using Deep Learning, the authors developed MCSNet+, an enhanced convolutional neural network (CNN) model incorporating Soft Non-Maximum Suppression (Soft-NMS), Position-Sensitive Prediction Modules (PSPM), and optimized anchor boxes to improve detection accuracy and speed. The model used is based on the Faster R-CNN architecture with modifications for improved small-object detection, leveraging pre-trained CNNs such as VGG16, ResNet50, and a custom MCS structure. The data type includes over 26,000 annotated images of pests collected from both laboratory and real warehouse environments.

The research problem tackled in [76] is the accurate classification of different rice varieties, which is essential for quality control in agriculture but traditionally done manually, leading to inefficiencies. The authors employed Deep Learning techniques to automate this process, focusing on two models: Vanilla Convolutional Neural Network (CNN) and VGG16, a widely used pre-trained deep learning architecture. The data type consists of a large dataset of 75,000 RGB images (250×250 pixels) of five rice varieties Basmati, Jasmine, Arborio, Ipsala, and Karacadag—each represented by 15,000 images.

This article [77] addresses the research problem of automating maize grain quality assessment. The authors apply deep learning methods to improve accuracy and efficiency in classification. Specifically, they use Convolutional Neural Networks (CNNs), with transfer learning applied to VGG-16 and VGG-19 models. The system is trained on a balanced dataset of 2,500 maize grain images categorized into five quality levels: Excellent, Good, Average, Bad, and Worst.

Table 1.1 provides a consolidated overview of recent deep learning applications in the classification of grain images, highlighting the models used, datasets and evaluation metrics.

Ref	**Research Problem**	**Deep Learning Model Used**	**Data Type**	**Results**
[66]	Identification of wheat varieties for seed testing	DenseNet201, Inception V3, MobileNet (transfer learning)	31,606 single-grain images, 4 varieties (Algeria)	DenseNet201 achieved 95.68% accuracy; Inception V3: 95.62%, MobileNet: 95.49%
[67]	Barley variety classification with limited samples	VGG-16 with SVM and softmax classifiers	Front/back images of barley varieties	Best: 94% accuracy (SVM with feature fusion); cross-validation avg: 94%
[68]	Automating grain quality inspection	ResNet-50 + SE, VGG19, Inception-v3, ResNet-152	350,000+ RGB single-kernel images (wheat, rice, maize, sorghum)	F1-score up to 99.9% for wheat , 97.2% for maize, 96.8% for sorghum, and 94.1% for rice.
[69]	Rice variety classification (similar appearance)	ARVDC-QIMFODL (CNN + QIMFO), LSTM	5 rice varieties (image dataset, 70/30 split)	Accuracy up to 99.66%; robust even with 30% training data
[70]	Pollen segmentation/classification with weak labels	U-Net + DenseNet + Grad-CAM	1324 SEM images, 3 pollen types	Accuracy: 86.6%, F1: 86%, Specificity: 93.2%, mIoU: 92.47%
[71]	Peanut variety classification for breeding	Improved VGG16 (GAP, BN, Inception module)	3365 scanned images of 12 peanut varieties	Accuracy: 96.7%; outperforms standard VGG16 (87.8%); F1 97.2%
[72]	Recognizing imperfect wheat grains	ResNet-50 + CBAM	RGB images (100×100 px), 6 wheat grain classes	Accuracy: 97.5%, F-measure: 96.12–99.5%
[73]	Rice variety classification (multi-stage)	DarkNet19 + SqueezeNet + BOA	75,000 RGB images, 5 rice types	100% accuracy (cubic SVM after feature fusion and selection)
[74]	Rice seed variety classification in Turkey	VGG, ResNet, EfficientNet, custom CNN	6833 microscope images, 5 rice varieties	Best accuracy: 97% (VGG); custom CNN close second
[75]	Detection of wheat storage pests	MCSNet+ (Faster R-CNN + Soft-NMS + PSPM)	26,000+ annotated pest images (real & lab)	mAP: 94.27% (Tribolium), 92.67% (Sitophilus)
[76]	Rice variety classification	Vanilla CNN vs VGG16	75,000 RGB images (5 rice varieties)	VGG16: 99.5% accuracy vs Vanilla CNN: 95.3%
[77]	Maize grain quality assessment	VGG-16, VGG-19 (transfer learning)	2500 images, 5 quality levels	VGG-16: 92% accuracy, VGG-19: 90%

Table 1.1: Summary of Deep Learning Application in Grain Image Classification

1.5 Agricultural Ontologies: Knowledge Modeling for Heterogeneity Problem

In complex systems such as agricultural supply chains, data is often generated from diverse sources, formats, and domains, leading to significant heterogeneity issues. This heterogeneity can hinder seamless data integration, interoperability, and effective decision-making. Ontologies offer a powerful solution to this challenge by providing a formal, structured representation of knowledge that enables semantic interoperability among heterogeneous data sources [78].

To conduct a comprehensive review on the use of ontology in agriculture, we performed a structured search using the query "Existing Agricultural Ontologies" on the Mendeley database. This search initially returned 110 papers. From this set, we filtered 99 articles published in scientific journals and conference proceedings. We then narrowed the selection to papers published between 2019 and 2023, resulting in 36 articles. To ensure accessibility and reproducibility, we prioritized open access publications, which reduced the number to 19 articles. After a thorough reading and critical evaluation of these documents, we identified 6 papers as highly relevant to our specific area of interest:

The article [79] presents an agricultural ontology specifically developed for the Saudi context, named SAAONT. The main objective is to structure and standardize agricultural terminology in the Arabic language, while providing a semantic knowledge base capable of supporting intelligent decision-making systems. This initiative addresses two major gaps: the lack of technological tools in the Saudi agricultural sector, and the absence of ontologies tailored to the local language and context. The developed ontology enhances the retrieval of accurate and relevant information for decision-makers and farmers, thus contributing to the establishment of a more intelligent, sustainable, and context-aware agriculture in Saudi Arabia.

The article [80] presents an extension of the ONTAgri ontology by integrating it with a Service-Oriented Architecture (SOA) to support precision farming applications. ONTAgri is an agricultural ontology designed to represent domain knowledge related to crop production, pests, soil, weather, and other farming factors. However, to enhance its applicability in real-time decision-making systems, the authors propose coupling ONTAgri with web services within a service-oriented framework. This integration allows farmers and agricultural systems to access semantically enriched information through interoperable services, enabling more dynamic, personalized, and context-aware farming support. The extended system improves data sharing, reusability, and interoperability across agricultural platforms, aiming to support precision agriculture by providing timely and relevant recommendations based on environmental and crop data. The proposed approach demonstrates how semantic technologies, combined with SOA, can bridge the gap between ontological knowledge and practical smart farming solutions.

This paper [81] addresses the problem of integrating heterogeneous agricultural data, which often come from diverse sources such as weather stations, farm management systems, and remote sensors, and are expressed in different formats and semantics. This heterogeneity poses a significant barrier to data interoperability and reuse. To solve this issue, the authors propose the use of semantic technologies specifically ontologies, RDF (Resource Description Framework), and SPARQL queries to semantically structure and integrate agricultural data. Their method involves aligning data from various sources through a semantic layer, enabling consistent representation and improved accessibility. The study is conducted within the context of French agriculture, illustrating real use cases relevant to the local agricultural system. The proposed approach demonstrates how semantic integration can facilitate better data sharing, enhance decision making, and support the development of intelligent farming systems. Although the article does not include a formal experimental evaluation, it contributes by presenting a conceptual framework and practical perspectives for applying semantic technologies in agriculture.

The article [82] presents an open platform based on ontologies aimed at improving semantic and syntactic interoperability of agricultural data from Internet of Things (IoT) sources. The work focuses on the use of crop-specific trait ontologies, particularly for hazelnuts, to structure and annotate data collected from wireless sensor networks, weather stations, and other agricultural systems. The system includes ontology-based data acquisition forms, mapping rules linking sensor data to ontology concepts, and web services for data exchange between different applications. The data is stored in formats compatible with the semantic web (RDF/XML, JSON, CSV). This approach enables better integration, visualization, and utilization of agricultural data, promoting smarter and more interoperable precision agriculture. Although developed for hazelnut cultivation, the method can be adapted to other crops by creating specific ontologies.

[83] Post-harvest loss is a major challenge in intelligent agriculture, especially for fruits like the Sekai-ichi apple, which is highly prone to diseases and experiences significant wastage during the post-harvest stage. To address this issue, the authors propose an ontology-enabled Internet of Things (IoT) framework that uses a hierarchical model to improve the detection and separation of damaged fruits. This model operates on three levels: the lower level involves manual separation and reliability detection, the middle level handles variations by reducing overfitting and improving adaptability, and the upper level refines fruit classification through image segmentation. The system uses a method called Boosted Continuous Non-spatial whole Attribute Extraction (BCNAE) to extract image features such as area, compactness, entropy, and moments from 3D sensor images. These features are structured into an ontology that supports precise identification of damaged areas using a region-based RIGS algorithm.

This article [84] presents the design and development of RiceMan, an ontology based expert system for identifying rice diseases and recommending appropriate treatments. The authors developed two ontologies—RiceDO and TreatO v2 based on trusted agricultural sources to represent rice disease symptoms (including pest-related issues) and corresponding control measures. RiceMan integrates these ontologies and employs ontology-based reasoning by composing user observations to diagnose diseases and suggest suitable treatments. The system was evaluated through practical tests with four stakeholder groups in Thailand, including ontology experts, senior and junior agronomists, and agricultural students. Evaluation results showed that the ontologies were consistent and the system was effective in assisting with disease diagnosis, though some vocabulary enhancements were recommended.

Table 1.2 provides a summary of existing agricultural ontologies, highlighting their main objectives, domains of application, and key features relevant to knowledge modeling in smart farming and agri-food systems.

1.6 Conclusion

In this chapter, we explored the multifaceted challenges associated with wheat grain storage and highlighted the critical need for intelligent, real-time monitoring systems. We first examined the factors that contribute to storage losses, including pests, moisture, and temperature fluctuations, which significantly impact grain quality.

To address these challenges, we reviewed a synergy of emerging technologies that enable smarter and more adaptive storage systems. The Internet of Things (IoT) offers a scalable

Ref	Research Problem	Ontology/Method	Purpose
[79]	Lack of technological tools and context-specific ontologies in Saudi agriculture	SAAONT (Agricultural Ontology)	Structure and standardize agricultural terminology in Arabic, support intelligent decision-making systems, and enhance information retrieval for farmers.
[80]	Need for real-time decision-making systems in agriculture	Extension of ONTAgri ontology with Service-Oriented Architecture (SOA)	Enhance data sharing, reusability, and interoperability for precision farming through semantic web services.
[81]	Integration of heterogeneous agricultural data from various sources	Use of semantic technologies (RDF, SPARQL)	Facilitate semantic data integration and improve decision-making and accessibility in agriculture.
[82]	Lack of interoperability for agricultural data from IoT sources	Ontology-based platform for crop-specific trait ontologies	Improve the integration, visualization, and utilization of agricultural data from IoT sources.
[83]	Post-harvest losses due to fruit damage	IoT-enabled ontology framework for detecting and separating damaged fruits	Reduce post-harvest losses by improving detection accuracy and processing time.
[84]	Rice disease identification and treatment recommendations	RiceDO and TreatO v2 ontologies	Assist with rice disease diagnosis and treatment recommendations using ontology-based reasoning.

Table 1.2: Summary of Existing Agricultural Ontologies

solution for real-time environmental monitoring, while deep learning techniques provide advanced analytical capabilities for visual grain quality assessment. Additionally, semantic ontologies were presented as a means of encoding expert knowledge and supporting automated reasoning for informed decision-making.

These technologies establish a solid foundation for the development of an integrated system capable of perception, analysis, and intelligent response. Building upon the insights and technological components discussed in this chapter, the next chapter will present the proposed architecture, methodology, tools, and implementation details of our intelligent wheat grain storage system.

Chapter 2

Methods and Materials

2.1 Introduction

This chapter presents the methodological framework and technical components employed to realize the objectives outlined in this dissertation. The proposed intelligent wheat grain storage system integrates multiple technologies to address the challenges of quality monitoring, risk prediction, and decision support in wheat grain warehouses management.

In alignment with the primary goal of ensuring safe and efficient grain storage, the methods adopted in this work include the use of deep learning, semantic modeling, and mobile computing. First, we describe the used dataset of wheat grain images, followed by the training and optimization of the MobileNetV3 model for classifying grain health conditions. To address the heterogeneity of sensor data and enhance reasoning capabilities, we present the development of a domain-specific agricultural ontology, enriched with Semantic Web Rule Language (SWRL) rules to infer storage risks dynamically.

In addition, this chapter details the design of the architecture used for real-time data acquisition, involving environmental sensors and imaging devices. Finally, we explain the development of a user-friendly mobile application that enables users to interact with the system, monitor storage conditions, and receive timely alerts.

2.2 Image Dataset Description

In this study, we used the GrainSet dataset [68] for the classification of image wheat grain. This dataset contains high-resolution images of individual wheat grains, extracted from a larger collection of more than 350,000 images that also includes maize, sorghum, and rice. Each grain was photographed from top and bottom views using a specialized optical imaging device, and manually annotated by expert inspectors. The dataset used comprises a total of 200,000 images distributed across eight grain quality categories. The largest portion of the dataset corresponds to normal (NOR) grains, accounting for 120,000 images, which reflects a significant representation of healthy samples. The remaining images are evenly distributed among various defect classes, each representing specific quality issues (Figure 2.2). These include 13,000 images each for Fusarium & Shriveled (F&S), Sprouted (SD), Moldy (MY), and Pest Attacked (AP) grains. The Broken (BN) category includes 14,500 images, while Black Point (BP) and Impurities (IM) are represented by 3,500 and 10,000 images respectively. This distribution ensures sufficient representation of both normal and defective grain types, enabling robust deep learning-based classification and quality assessment.

The use of this dataset is further justified by the limited availability of open-access, high-quality datasets dedicated to wheat grain classification in existing literature. Exist-

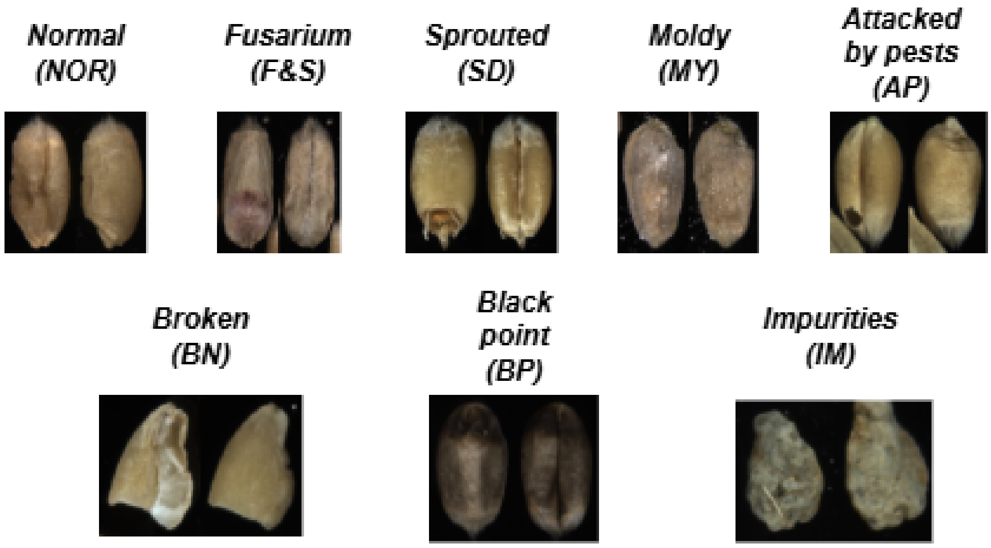

Figure 2.1: Examples of Dataset Classes

ing (Section 1.4.2) studies in the field of grain quality assessment employ proprietary or institution-specific datasets that are not publicly available, which hinders reproducibility and comparative evaluation of deep learning approaches. In contrast, the dataset used in our study provides a large-scale, well-annotated collection of 200,000 images covering a wide spectrum of real-world grain quality categories. This makes it particularly valuable for training and validating deep learning models aimed at automating quality inspection processes. Its comprehensive coverage of both normal and defective grains ensures that the model can generalize across diverse conditions, thus supporting the development of a robust and scalable intelligent grain monitoring system.

All images are resized to a fixed resolution of $224 \times 224 \times 3$, which matches the standard input size expected by the MobileNetV3-Large model. This resizing ensures uniform processing of images with varying original dimensions, while preserving the general proportions of the objects within the image.

2.3 Deep Learning Classification

In this work, we adopt MobileNetV3-Large as the backbone convolutional neural network for image-based wheat grain classification, due to its excellent trade-off between accuracy, speed, and computational efficiency key requirements for real-time mobile deployment. MobileNet belongs to a family of lightweight deep learning models specifically designed for mobile and embedded vision applications, where computational resources are often limited.

The original MobileNet architecture [52] introduced the concept of depthwise separable convolutions, which decompose the standard convolution operation into two simpler steps: a depthwise convolution (applying one filter per input channel), followed by a pointwise 1×1 convolution (to combine outputs across channels). This design significantly reduces the number of parameters and floating-point operations, making the model compact and efficient for edge devices such as smartphones and IoT-based systems. Furthermore, MobileNet incorporates width and resolution multipliers, enabling users to adjust the model's depth and input resolution to balance accuracy against computational cost.

Subsequent improvements came with MobileNetV2 [85], which introduced inverted residual blocks and linear bottlenecks to enhance information flow and memory efficiency. In this architecture, each block first expands the feature space using a lightweight convolution, processes it using a depthwise separable convolution, and projects it back to a lower-dimensional space through a linear 1×1 convolution, omitting non-linear activation in the bottleneck layer to preserve representational power.

MobileNetV3 [86], the latest evolution, combines architecture search with manual tuning to optimize both performance and efficiency. It incorporates the structural advantages of MobileNetV2 while adding Squeeze-and-Excitation (SE) modules to better capture inter-channel dependencies, as well as the h-swish activation function, which improves performance while remaining hardware-friendly. MobileNetV3 is available in two versions: Small, designed for ultra-low-latency applications, and Large, optimized for tasks requiring higher accuracy.

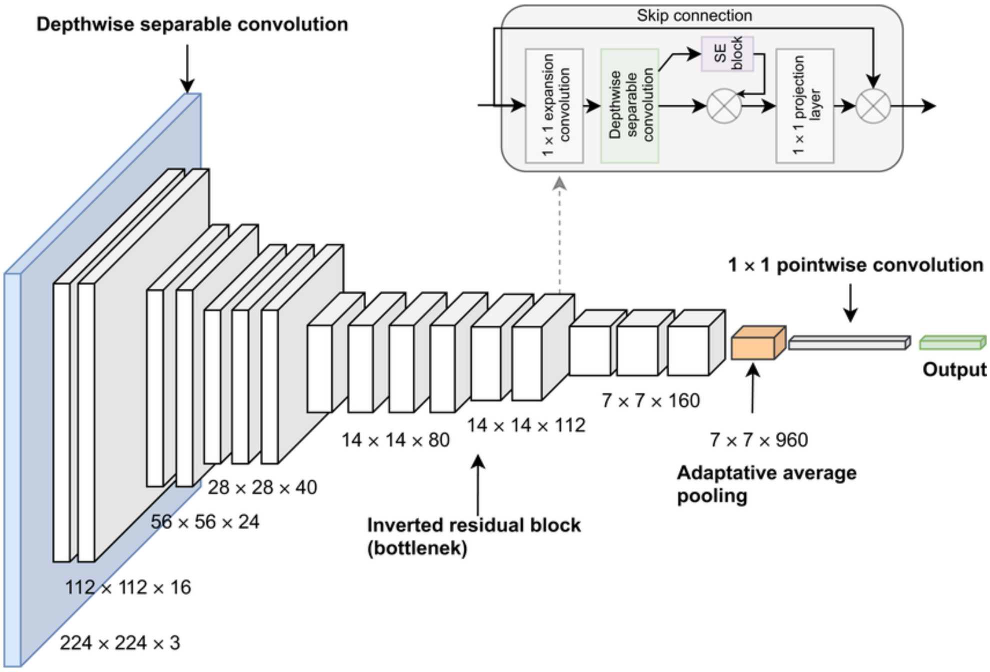

Figure 2.2: A structure of MobileNetV3
[1]

The architecture of MobileNetV3-Large consists of three main components: an initial standard convolution layer, followed by a sequence of bottleneck blocks with SE and h-swish enhancements, and a final classification head. This design ensures efficient feature extraction and accurate classification with minimal resource consumption—perfectly aligned with the goals of our mobile-based grain monitoring solution.

1. Input Layer

– Input: RGB image resized to $224 \times 224 \times 3$

– A 3×3 convolution layer with 16 filters and stride 2

– Followed by Batch Normalization and Hard-Swish activation

2. Bottleneck Blocks (B1)

MobileNetV3-Large contains 15 bottleneck blocks, each with varying parameters:

– Kernel sizes: mostly 3×3 or 5×5

[1] https://www.researchgate.net/figure/The-MobileNetV3-architecture-and-its-core-components_fig4_375462137

- Expansion factors: up to 6× the number of input channels
- Output channels: from 16 up to 160
- SE blocks: applied in some layers (Squeeze-and-Excitation for attention)
- Activations: ReLU and Hard-Swish, depending on the block
- These blocks perform:
  - Depthwise convolutions for efficient spatial filtering
  - Pointwise convolutions (1×1) for channel mixing
  - Residual connections (skip connections) when possible
- The sequence of blocks allows the network to learn increasingly abstract and complex features

3. Final Convolution Block (B2)

- After the bottleneck blocks, a 1×1 convolution layer increases the number of channels to 960
- Followed by Batch Normalization and Hard-Swish activation

4. Classification Head (B3)

- A Global Average Pooling layer compresses spatial dimensions (H×W) to 1×1
- Two fully connected layers (implemented as 1×1 convolutions):
  - The first expands the features to 1280
  - The second projects down to the number of classes (e.g., 8 in our case)
- Final activation is Softmax to produce class probabilities

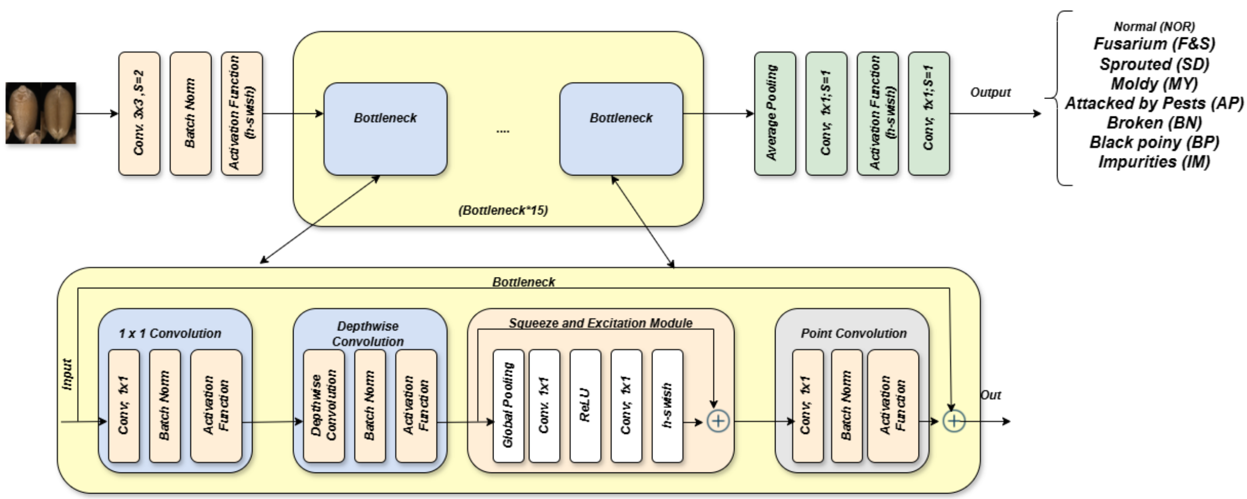

Figure 2.3: A structure of MobileNetV3-Large

2.4 Experimental Setup

The experiments were conducted on the workstation DESKTOP-38CR7NV, running Windows 11. It is equipped with dual Intel(R) Xeon(R) Gold 6138 CPUs, each operating at 2.00 GHz, and features 128 GB of RAM. The system has a 64-bit architecture with an x64-based processor.

The model was trained from scratch using two subsets: a training set comprising 80% of the data (180,000 images) and a testing and validation set comprising the remaining 20% (20,000 images). Hyperparameter values were selected empirically based on insights gained through extensive experimental testing. Various combinations were explored to identify those that provided the best generalization across different datasets while minimizing the risk of overfitting. The optimization algorithm employed was Adaptive Moment Estimation (Adam [87]) with its default parameters.

Hyperparameters Description

Batch Size

Batch size refers to the number of samples processed simultaneously during a single training iteration. It has a direct impact on both training efficiency and memory consumption. While larger batch sizes can accelerate training, they also demand more computational resources.

Epoch

An epoch refers to one complete pass through the entire training dataset. This option specifies the number of epochs to be used during training.

Learning Rate

The learning rate determines the step size used by the optimizer to update the model's weights during training. A learning rate that is too high may cause the model to overshoot the optimal solution, while a rate that is too low can result in slow convergence.

Optimizer

An **optimizer** is an algorithm used to update the weights of a neural network in order to minimize the loss function during training. Its main goal is to improve the model's performance by reducing prediction errors. Optimizers determine how the model's parameters are adjusted at each step based on the gradients computed through backpropagation. There are different types of optimizers, such as:

- **SGD (Stochastic Gradient Descent)** – updates weights using a fixed learning rate and a single or small batch of samples.
- **Adam (Adaptive Moment Estimation)** – combines momentum and adaptive learning rates for faster and more efficient convergence.
- **RMSprop** – maintains a moving average of squared gradients and adapts learning rates accordingly.

A summary of the tested hyperparameters and the final chosen values is presented in Table 2.1.

Hyperparameter	Values Explored	Selected values
Batch size	8, 16, 32, 64, 128, 256	64
Epochs	1,2, .. .,1000	301
Learning rate	0.000001, 0.00005, 0.00002, 0.00001, 0.0005, 0.0002, 0.0001, 0.005, 0.002, 0.001, 0.01	0.00005

Table 2.1: Hyperparameters configuration

2.5 Evaluation and Results

Evaluation metrics

To evaluate the proposed system, we employed various classification performance metrics, including:

Confusion matrix

The confusion matrix [88] is a fundamental tool in predictive analytics for evaluating the performance of classification models. It provides a summary of the model's prediction results by displaying the number of correct and incorrect predictions in a tabular format.

Specifically designed for classification tasks, especially binary classification, the confusion matrix takes the form of an N x N square matrix, where N is the number of target classes. In this matrix, rows typically represent the predicted classes, Columns represent the actual (true) classes. By examining the diagonal elements of the matrix, one can identify the number of correct classifications. Off-diagonal values indicate the types and frequency of misclassifications, offering insight into the model's behavior. The confusion matrix includes the following key components:

True Positive (TP): The model correctly predicted the positive class.
False Positive (FP): The model incorrectly predicted the positive class .
False Negative (FN): The model incorrectly predicted the negative class.
True Negative (TN): The model correctly predicted the negative class.

Precision

refers to the proportion of correctly identified positive instances among all instances that the model has labeled as positive. It is computed by dividing the number of true positives by the sum of true positives and false positives:

$$Precision = \frac{TP}{TP + FP}$$

This metric indicates how accurate the model's positive predictions are.

Recall

also known as sensitivity, measures the proportion of actual positive instances that are correctly identified. It is calculated by dividing the number of true positives by the sum of true positives and false negatives:

$$Recall = \frac{TP}{TP + FN}$$

This metric reflects how well the model is able to identify all relevant cases within a dataset.

Loss Function

A **loss function** is a mathematical function that measures the difference between the predicted output of a model and the actual target value. It quantifies how well or poorly the model is performing during training. The goal of training a neural network is to minimize this loss function, thereby improving the model's predictions.There are different types of loss functions depending on the task; in our system, we used the Categorical Cross-Entropy loss.

Accuracy

Accuracy is a fundamental metric used to evaluate the performance of a model. It represents the *proportion of correct predictions* out of the *total number of predictions made*. This includes both **true positives** (TP) and **true negatives** (TN), meaning the instances correctly identified by the model. Accuracy is calculated using the following formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

F1-score

The **F1 score** is the harmonic mean of *precision* and *recall*. It is particularly useful when dealing with imbalanced datasets, as it provides a balance between the two metrics. A perfect F1 score of 1.0 indicates that the model has achieved both perfect precision and perfect recall, while a score of 0.0 means very poor performance in one or both aspects.

The F1 score is calculated using the following formula:

$$F1Score = \frac{2 \cdot (Precision \cdot Recall)}{Precision + Recall}$$

Table 2.2 presents the accuracy and loss values obtained for the training and testing sets. Figure 2.4 illustrates the progression of the training loss and accuracy over the epochs. From Figure 2.4, it can be observed that the model's accuracy increases rapidly during the initial epochs and finally stabilizes after 301 epochs, reaching its optimal performance of 99.27%. The loss function follows an inverse curve, decreasing steadily during the initial epochs, then stabilizing and eventually reaching its minimum value of 0.0226.

For the testing set, the model achieves an accuracy of 98.33% and successfully minimizes the loss to 0.0574. The accuracy is distributed across the classes, as shown in the confusion matrix in Figure 2.5. As observed, the individual class accuracies are well aligned, indicating consistent performance across different classes. In order to identify the classification errors made by the model, we thoroughly examined the misclassified images for each of the eight classes. We found that the highest misclassification error occurred in the AP class. The images from this class often contain small holes caused by pests, which are not clearly visible. This lack of clarity leads the model to misclassify them as NOR or, in some cases, as SP, due to the visual similarity between pest-induced holes and those caused by the early stages of sprouting. We found another significant misclassification error in the MY class. Images of wheat containing small powdery spots were misclassified as F&S, likely due to the visual similarity between the grain curling patterns and those found in F&S samples. The misclassification errors in the F&S class occur in images containing grains with pronounced curling, which appear similar to the holes caused by pests in the AP class. The misclassification in the NOR class occurs in images of grains with an indented lower edge, which visually resembles the edge damage caused by pests in the AP class. As a result, these grains are often misclassified as AP. The misclassification error in the SD class occurs in images of grains that often exhibit early stages of sprouting. These visual characteristics resemble grains from the AP class, which have small holes caused by pests. However, a few misclassifications were observed in classes such as BP, BN, and IM. Overall, the model demonstrates near-perfect classification performance for these classes, with the few errors primarily occurring in images that lack clear or distinctive class-specific features

	Accuracy	**Loss**
Train	0.9927	0.0226
Test	0.9833	0.0574

Table 2.2: Performance on training and testing sets

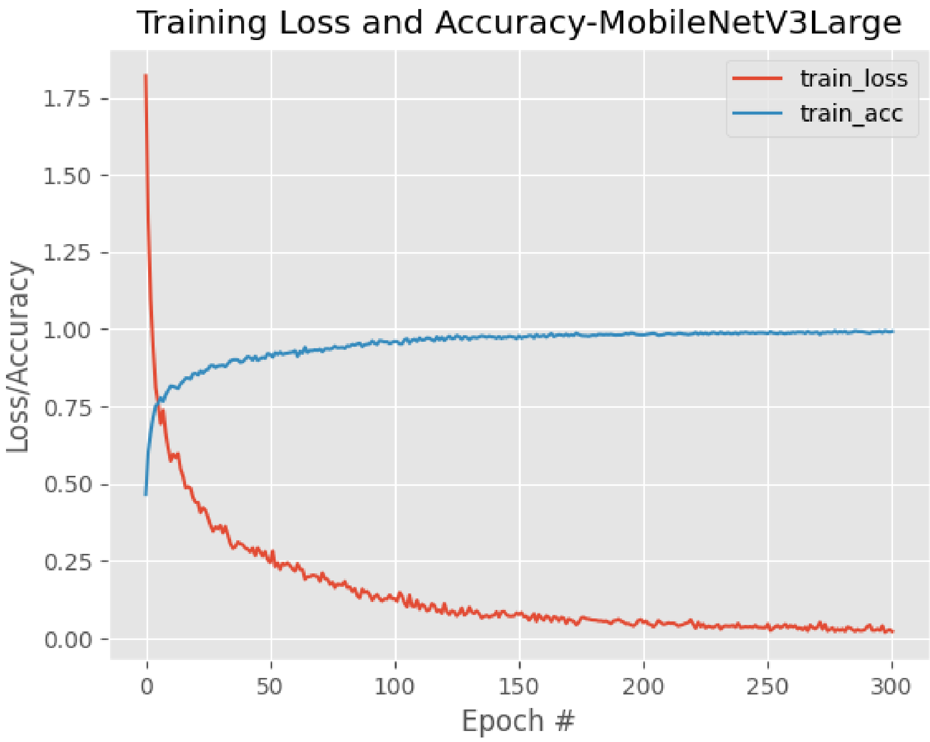

Figure 2.4: Training set loss and accuracy progression

The dataset exhibits some imbalance, as shown in Table ??. To understand the effect of this imbalance, we carried out a more detailed analysis of the model's performance. Along with the confusion matrix results, we evaluated the model using three main metrics: precision, recall, and F1 score. Table 2.3 presents the results for these metrics. A recall value of 0.9833 shows that the model identifies about 98.33% of all actual positive cases. A precision of 0.9832 means that when the model predicts a positive class, it is right about 98.32% of the time. The F1 score, at 0.9831, confirms that the model keeps a strong balance between precision and recall. The close values of precision, recall, and F1 score indicate a well-balanced classification performance.

As shown in Figure 2.5, the accuracy of the majority class, Normal (NOR), is not the highest. The minority classes, like Black Point (BP) and Insect Damage (IM), do not have the lowest accuracies. This indicates that the model does not demonstrate a strong bias toward the majority class and is capable of effectively recognizing minority classes. In addition, we analyze false positives (FP) (last ligne) and false negatives (FN) (last column) across all classes. We found that the majority class, Normal (NOR), has a small number of false positives. This means the model does not often misclassify other classes as Normal.

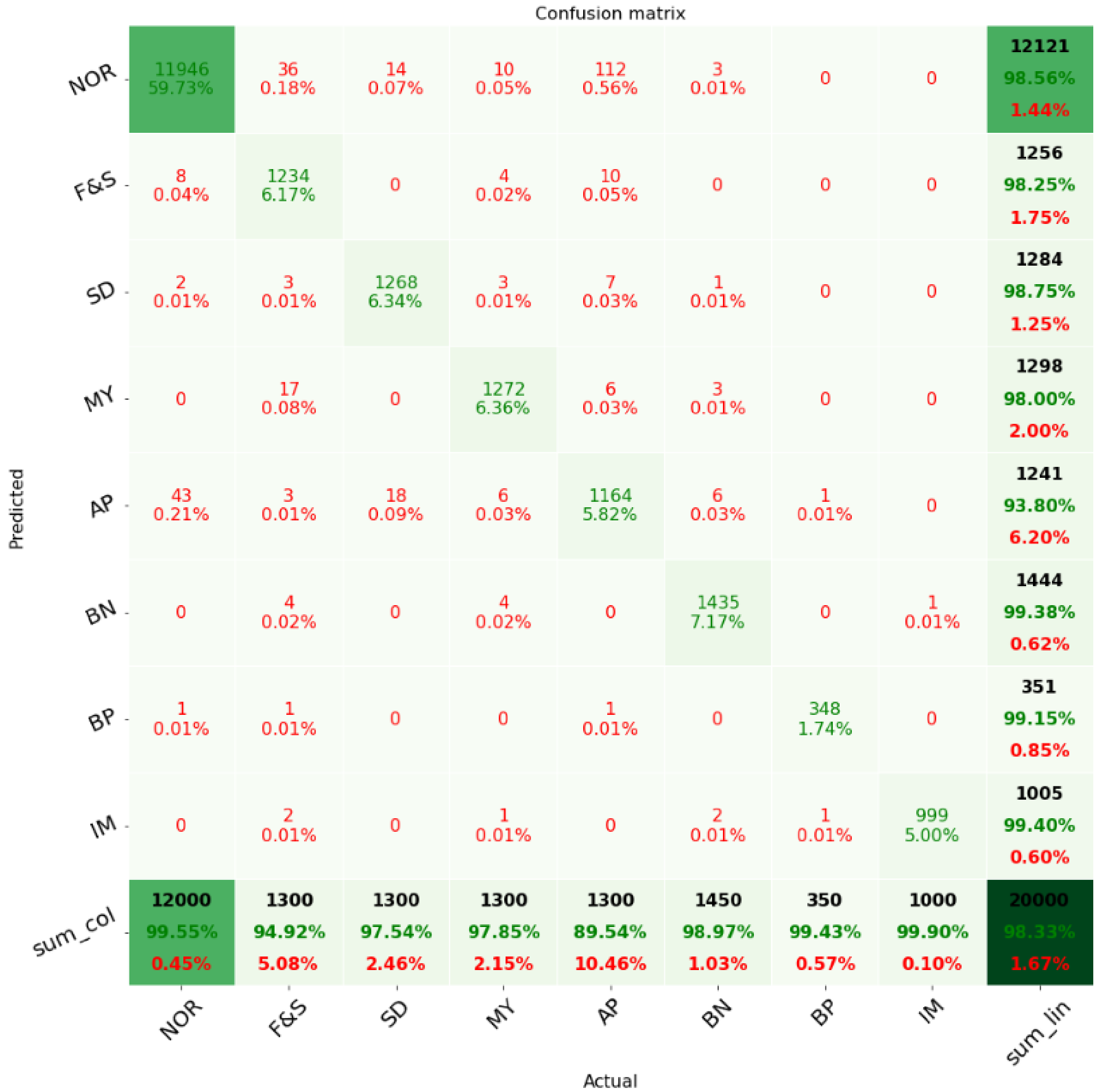

Figure 2.5: Confusion matrix

It shows that there is no bias toward the majority class and that the model can clearly distinguish NOR from other classes, even when there is class imbalance. On the other hand, the minority classes, like Black Point (BP) and Impurities (IM), have few false negatives. This shows that the model can correctly classify most examples of these minor classes. It demonstrates its ability to recognize and differentiate minority class instances from others, despite their limited presence in the dataset.

	F1-score	**Precision**	**Recall**
Test	0.9831	0.9832	0.9833

Table 2.3: Performance on testing set

2.5.1 Model Testing

To evaluate the model in a real-case scenario, a single image was provided as input. The model performed inference and predicted the corresponding class. In this example, the predicted class is NOR, indicating that the image was classified as normal by the model. This test confirms that the prediction pipeline image loading, preprocessing, inference, and result display is functioning correctly.

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 2s 2s/step
 Predicted Class: NOR
```

Figure 2.6: Model classification result for a test image

2.6 Ontology Development

The ontology forms the knowledge backbone of our smart storage system, providing a semantic framework that integrates heterogeneous data streams – including MobileNetV3 defect classifications from the GrainSet dataset and real-time IoT sensor networks – into a unified reasoning environment. Built using Methontology, this domain model enables context-aware decision automation through SWRL rules by formally representing key entities and their relationships.

2.6.1 Domain definition and objectives

This ontology aims to create an intelligent decision-support system that integrates MobileNetV3 outputs, real-time IoT environmental monitoring, and expert domain knowledge into a unified semantic framework.

Its primary purpose is to prevent wheat grain disease in storage facilities by enabling automated, context-aware interventions through SWRL reasoning rules.

2.6.2 Information Collection

The development of the agricultural ontology for intelligent wheat grain storage was grounded in a rigorous and multi-source information collection phase. This process began with a comprehensive review of scientific literature, including peer-reviewed journal articles, academic theses, and technical reports related to wheat storage, grain quality assessment, and post-harvest management [89] [90]. These sources provided foundational theoretical knowledge and helped identify core domain concepts, such as storage conditions, quality parameters, degradation risks, and operational practices.

To complement the theoretical insights, a professional internship was conducted at the Directorate of Cereals and Pulses (Direction des Champs et des Légumineuses) in the province of Guelma. During this internship, practical experience was acquired within the quality control department, where various aspects of wheat storage management were directly observed. This included batch inspection protocols, classification criteria, environmental condition monitoring, and infrastructure handling procedures. First-hand exposure to operational challenges—such as maintaining optimal humidity and temperature ranges to prevent spoilage—helped bridge the gap between academic knowledge and field realities. This practical engagement significantly enriched the ontology development process by ensuring that the modeled knowledge reflects both scientific standards and operational needs.

Competency Questions for Ontology Development

Before initiating the formal construction of the ontology, a set of competency questions was defined. These questions serve as a methodological tool to guide ontology design by outlining the scope, purpose, and types of reasoning the ontology must support. They also help ensure that the ontology aligns with real-world informational and decision-making needs within the domain of wheat grain storage.

General Questions

- What are the main conditions required to ensure proper wheat storage?
- Why is it important to control humidity during wheat storage?
- What are the risks associated with poor wheat storage?
- What are the economic impacts of wheat quality degradation during storage?
- How does climate variability influence wheat storage practices?

Questions about Humidity and Temperature

- What is the optimal humidity level for long-term wheat storage?
- How does temperature affect the quality of stored wheat?
- What tools or equipment can be used to monitor humidity and temperature in grain silos?
- What are the acceptable temperature and humidity ranges to avoid mold or pest proliferation?
- How frequently should environmental conditions be monitored in storage facilities?

Questions about Storage Infrastructure

- What are the differences between silo storage and warehouse storage?
- What materials are best suited for building grain silos, and why?
- How does the choice of storage infrastructure impact the shelf life of wheat?
- What design features can help improve air circulation in wheat storage?
- How can sensor-based monitoring systems be integrated into storage infrastructures?

Questions about Pest Management

- What are the most common pests in wheat storage, and how can they be prevented?
- What natural or chemical methods can be used to protect wheat stocks from infestations?
- How important is stock rotation in preventing pest infestations?
- What indicators suggest early stages of infestation?
- How can AI or IoT technologies assist in early pest detection and intervention?

Practical and Management Questions

- What are the main indicators of wheat deterioration during storage?
- Why is the first-in, first-out (FIFO) policy important in stock management?
- How does silo automation contribute to better wheat storage management?
- What types of data should be collected to optimize wheat preservation?
- How can ontology-based reasoning support decision-making in storage management?

This structured set of questions played a crucial role in shaping the ontology's structure, enabling it to effectively support semantic reasoning, early risk detection, and decision-making in smart grain storage systems.

2.6.3 Conceptualization and Implementation

The conceptualization stage of the ontology, which entails locating and organizing the essential ideas pertaining to wheat storage management, is covered in this section. The primary entities, their characteristics, and the connections between them are defined in light of the domain knowledge that has been acquired. Grain states, sensors, and possible storage issues are a few of these.

The hierarchical structure of the ontology's classes and their relationships, as created with Python using OWLready2 (Annexe 01) Library and visualised with Protégé, is shown in the Figure 2.7.

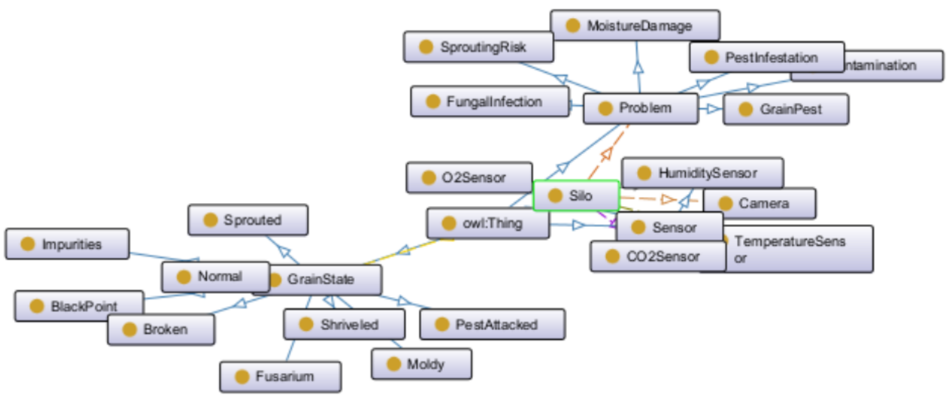

Figure 2.7: Hierarchical Representation of the Proposed Ontology with Protégé

To enable reasoning based on both sensor data and visual analysis, we integrate SWRL rules that leverage the outputs of the deep learning classification model. Specifically, the MobileNetV3-Large model classifies wheat grains into categories such as normal, moldy, sprouted, pest-attacked, or broken. These classification results are semantically annotated and injected into the ontology as instances of grain conditions. SWRL rules are then applied to combine this information with environmental parameters obtained from IoT sensors Figure 2.8.

```python
# SWRL Rules

with onto:

    # Détection de Grains Cassés
    rule1 = Imp()
    rule_1 = Imp()
    rule_1.set_as_rule("""Silo(?s), Camera(?c), hasCamera(?s, ?c), cameraValue(?c, "BlackPoint")
                        -> triggers(?s, PestInfestation)""")

    # Détection de Grains Cassés
    rule2 = Imp()
    rule_2 = Imp()
    rule_2.set_as_rule("""Silo(?s), Camera(?c), hasCamera(?s, ?c), cameraValue(?c, "Moldy")
                        -> triggers(?s, FungalInfection)""")

    rule3 = Imp()
    rule_3 = Imp()
    rule_3.set_as_rule("""Silo(?s), Camera(?c), hasCamera(?s, ?c), cameraValue(?c, "Impurities")
                        -> triggers(?s, Contamination)""")
```

Figure 2.8: Some SWRL Rules Implemented in Python

2.7 System Architecture

The architecture is composed of multiple functional layers, each responsible for a specific role. These components work collaboratively to acquire heterogeneous data, analyze it intelligently, and generate context-aware alerts and actions. Figure 2.9 illustrates the overall system workflow.

2.7.1 Data Acquisition Layer

The system begins with the acquisition of environmental and visual data from the warehouse. Two sources are involved:

- **IoT Sensors** continuously monitor critical environmental parameters such as temperature and humidity within the storage facility. These values are stored and transmitted to the system for semantic interpretation.
- **Cameras** are deployed to capture images of stored wheat batches. These visual inputs are used to assess grain quality and detect defects (e.g., mold, sprouting, pest damage).

2.7.2 Deep Learning Layer

Captured images are processed by a MobileNetV3-Large model, trained on a labeled Wheat Grain Dataset.

The model classifies the input images into predefined categories (e.g., normal, damaged, moldy) and produces classification results, which are passed to the reasoning layer. This step plays a crucial role in automating the quality assessment process.

2.7.3 Semantic Reasoning Layer

Both the classification results and sensor data are fed into the ontology. Based on predefined rules and semantic inference, the system can identify critical conditions—such as temperature anomalies, early signs of infestation, or batch degradation.

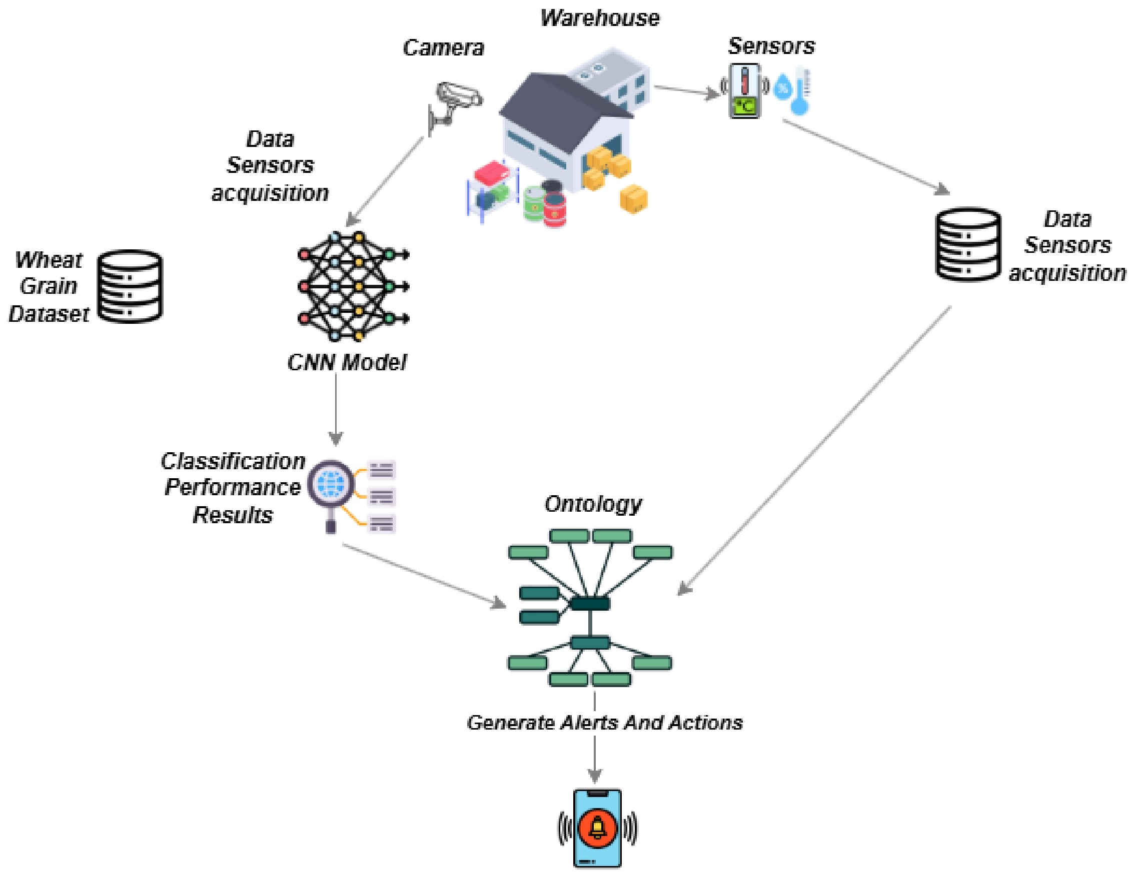

Figure 2.9: Achitecture System

2.7.4 Alert Layer

The final layer is responsible for generating alerts. When the ontology detects a risk or rule violation, it triggers an appropriate response. Alerts are delivered via a mobile application.

This architecture ensures that each component from data acquisition to reasoning contributes to a scalable, context-aware, and intelligent grain storage solution. It promotes automation, improves storage quality, and minimizes losses due to spoilage or late intervention.

2.8 Execution scenarios

In this section, we showcase the user interfaces for both the desktop and mobile iterations of the application. These interfaces have been crafted to provide a uniform user experience across various platforms. The subsequent screenshots demonstrate the primary features, arrangement, and interactions offered to users, emphasizing the application's effectiveness and adaptability in both desktop and mobile settings.

2.8.1 Desktop application

This is the initial screen of the SmartEpiStock dashboard. It provides access to the main silo operations, including options to create a new silo, analyze all silos, save the ontology, visualize data, and view the dashboard summary. The main display area is currently empty, waiting for user interaction.

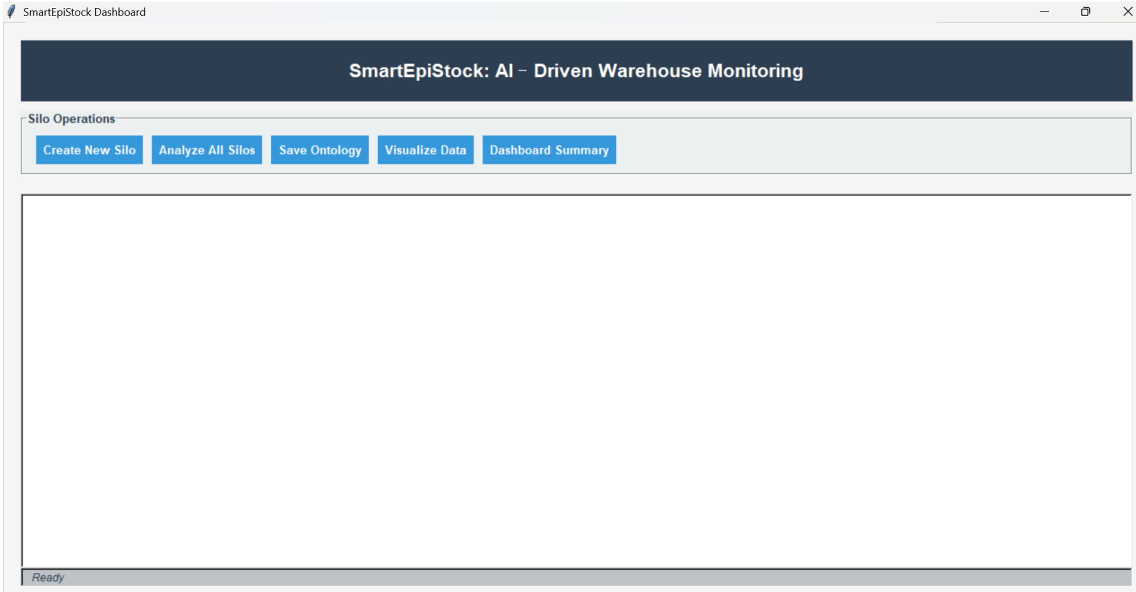

Figure 2.10: Initial SmartEpiStock interface displaying core AI-powered silo management controls before any silo creation.

After creating Silo 1, sensor data is now displayed, including temperature, humidity, CO2 concentration, O2 level, and a visual detection of "Fusarium" via camera input. The interface also adds two new operational buttons: Add Sensors and Analyze, allowing users to initiate analysis or configure sensor settings.

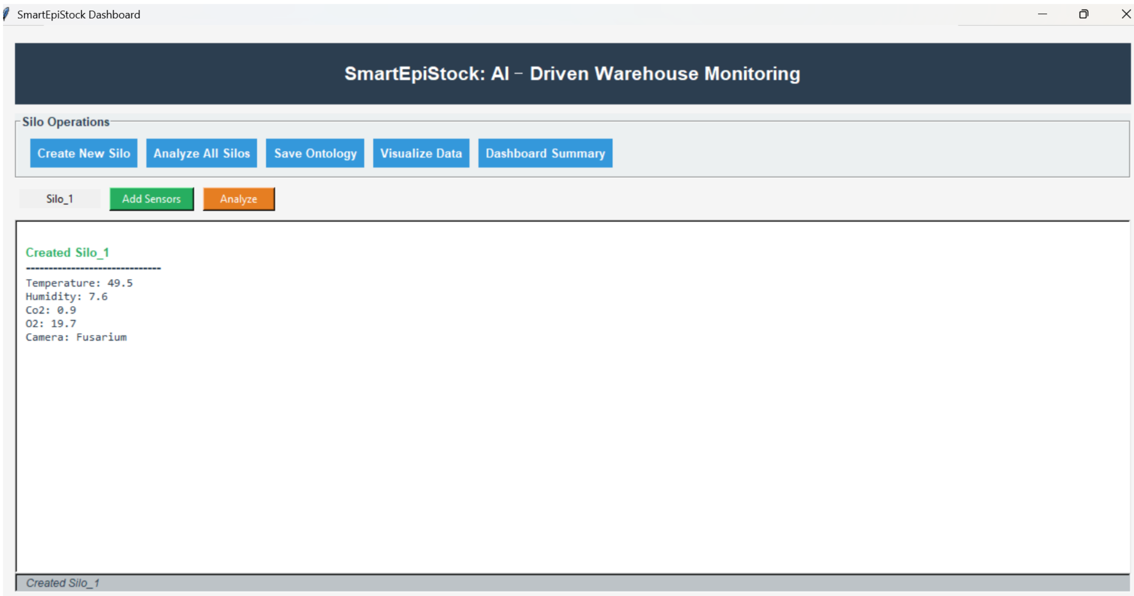

Figure 2.11: SmartEpiStock interface showing real-time environmental data and camera-based detection after creating Silo 1

This version of the interface allows users to add sensors at specific vertical levels within the silo, namely the middle and bottom. These options support advanced monitoring strategies by enabling AI to detect conditions at different depths of the grain storage.

After clicking the Analyze button for the silo, the system performs an AI-driven evaluation of the sensor data. In this version, the interface displays a warning or alert indicating

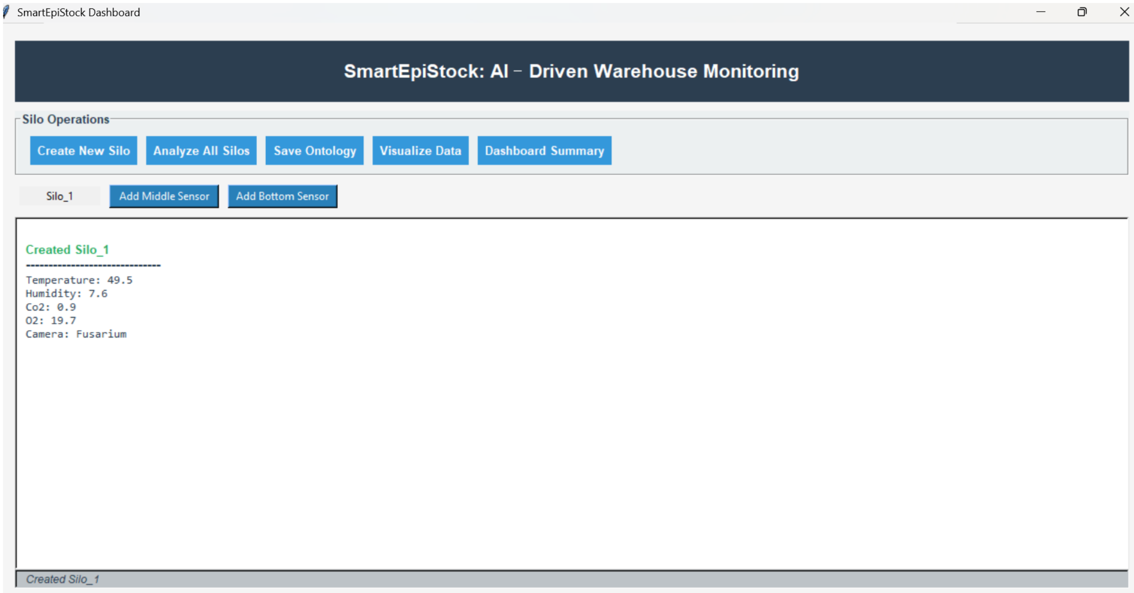

Figure 2.12: Advanced sensor setup interface enabling middle and bottom sensor placement within Silo$_1 forlayeredmonitoring$.

an issue (such as temperature too high, or Fusarium presence), helping users identify and take action on anomalies.

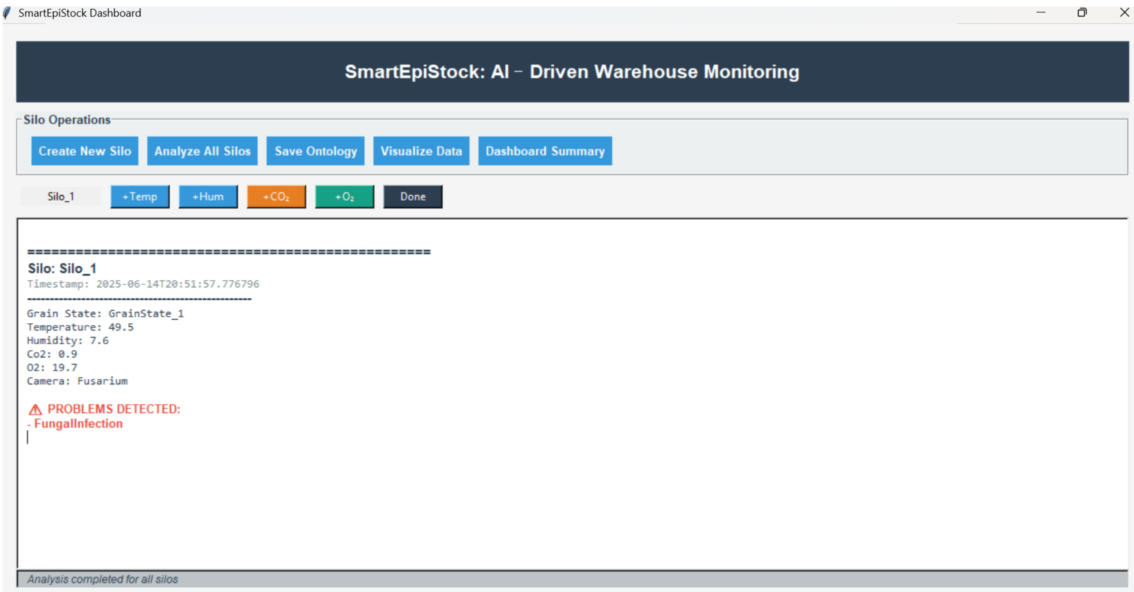

Figure 2.13: Silo 1 analysis results highlighting detected problems through AI, such as abnormal temperature or contamination alerts.

This interface is the Dashboard Summary view. It presents bar graphs for key environmental parameters such as humidity and temperature across all silos. It also categorizes the silos into status groups: Normal, Warning, and Danger, giving users a high-level overview of the overall silo health.

After clicking on Save Ontology, the system confirms the successful export or saving of the internal knowledge model used to describe silo structures, sensors, and anomalies. This ontology can be reused for reasoning, inference, or integration with semantic systems.

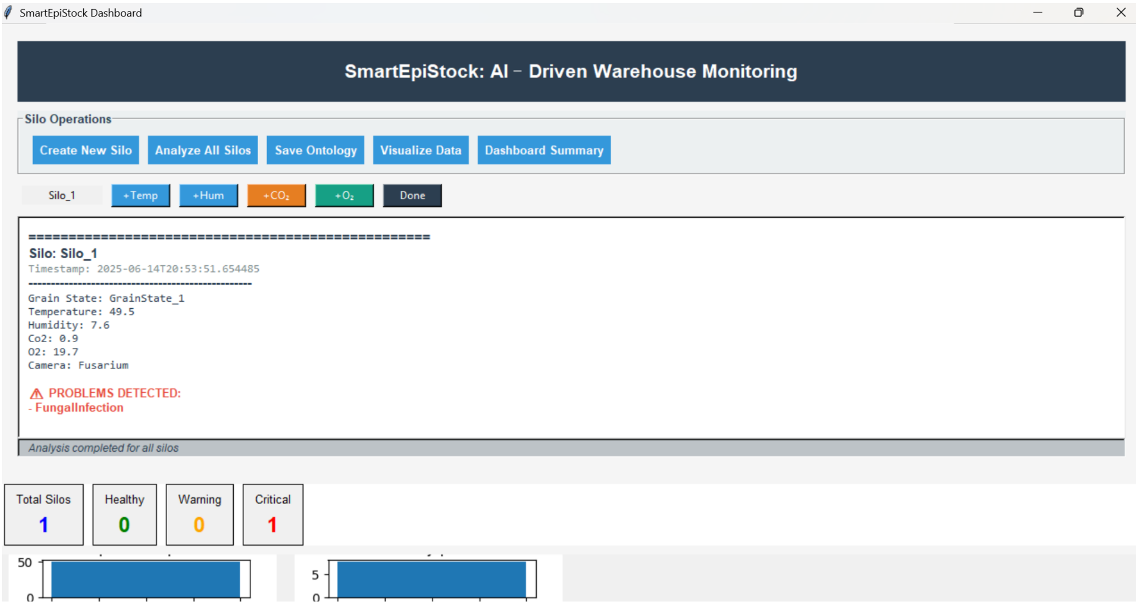

Figure 2.14: SmartEpiStock dashboard showing humidity and temperature charts, along with silo status categorization: Normal, Warning, and Danger.

2.8.2 Mobile application

This interface represents the homepage for new users wishing to create an account on the SmartEpiStock application. The screen offers a simple and uncluttered form, including two essential fields: email address and password. The orange button labeled "Register" allows you to confirm your registration after entering the required information.

This interface is designed for users who already have an account on the SmartEpiStock app. It displays a "Welcome Back" message followed by an email and password field. The blue Login button allows you to validate the information entered and access the app. For new users, a link at the bottom of the page titled "Sign Up" redirects them to the registration form.

This interface represents the home screen of the SmartEpiStock application when no silos have been created yet. The user is prompted to click the “Create Silo” button to get started. Other functionalities such as “Analyze Silos” and “View Charts” are disabled until at least one silo is added.

This figure shows the application state after the creation of the first silo. The options “Analyze Silos” and “View Charts” are now enabled. The displayed silo (Silo 1) includes environmental data such as temperature, humidity, CO2, and O2 levels, along with the camera type (“Shriveled”). There is also a button to add additional sensors to the silo.

This interface appears when the user clicks on “Add Sensors” for a specific silo. The user is given the option to add a sensor in the middle (“Add Middle Sensor”) or at the bottom of the silo (“Add Bottom Sensor”). A “Save” button allows the user to confirm the addition, while a “Cancel” button is available to abort the operation.

This interface appears when the user clicks on “Add Sensors” for a specific silo. The user is given the option to add a sensor at the bottom of the silo (“Add Bottom Sensor”) or in the middle section (“Middle Sensor”), where multiple types of sensors can be added, including temperature (“Add Temp”), humidity (“Add Humidity”), carbon dioxide (“Add CO”), and

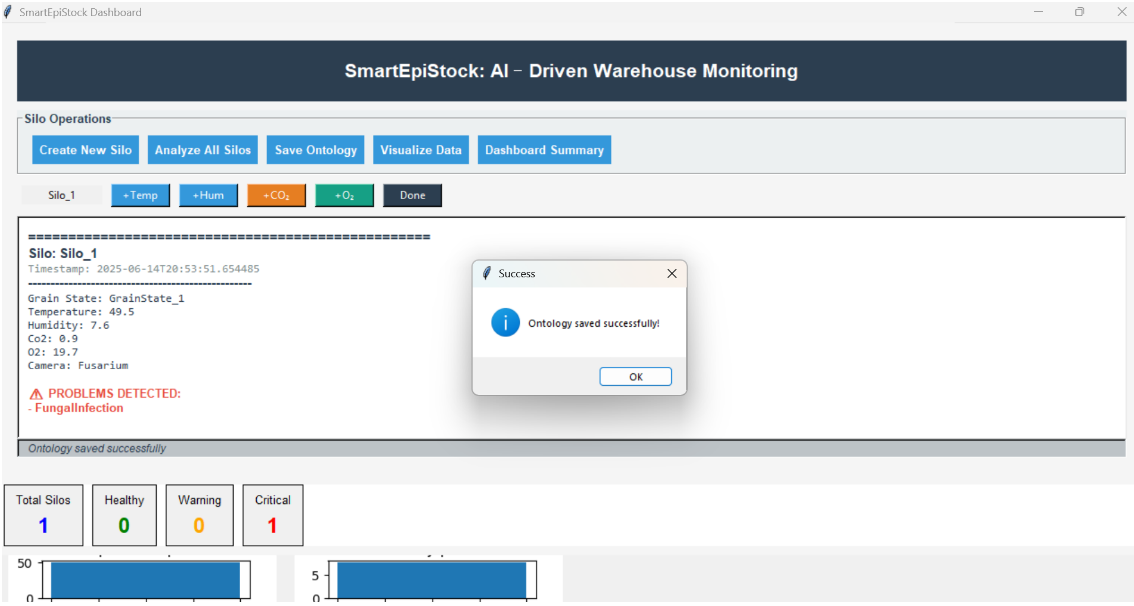

Figure 2.15: Confirmation interface showing that the ontology model of silo configurations and sensor data has been successfully saved.

oxygen (“Add O”). A “Save” button allows the user to confirm the addition of the selected sensors, while a “Cancel” button is available to abort the operation.

This interface provides a real-time overview of the environmental conditions inside the storage silos. At the top, three summary indicators are presented: Total Silos: Displays the total number of silos monitored (1 in this case). Good Silos: Indicates how many silos are currently in optimal conditions (1 in this case). Not Good: Shows the number of silos with abnormal or critical conditions (0 in this case). Below the indicators, a bar chart is used to visualize the values recorded for Silo 1: The red bar represents the temperature (28.21°C), The blue bar represents the humidity (17.18This visual representation allows users to quickly assess environmental conditions and detect any potential risks or anomalies in the silo.

This interface displays a detailed alert card for Silo 1, including environmental sensor readings and automatically generated alerts based on expert rules:
Camera Type: Fusarium (used for visual inspection of grain quality).
Temperature: 37.28°C
Humidity: 10.43
CO Level: 54.09
O Level: 55.19
The system has triggered the following alerts:
Temperature between 30–40°C: Indicates risk of mould growth and insect activity.
Humidity between 10–13%: Indicates favourable conditions for mould development.
Elevated CO level: Suggests possible fungal growth or lack of proper ventilation.
Visual inspection: Damaged or contaminated grains were identified (e.g., cracked kernels, discoloration, fungal spots).

2.9 Conclusion

This chapter has outlined the methodological foundations and technological building blocks of the proposed intelligent wheat grain storage system. By integrating deep learning for

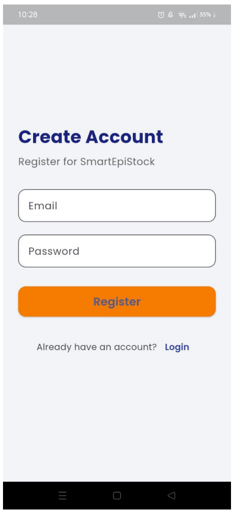

Figure 2.16: the home page for new users wishing to create an account on the SmartEpiStock application

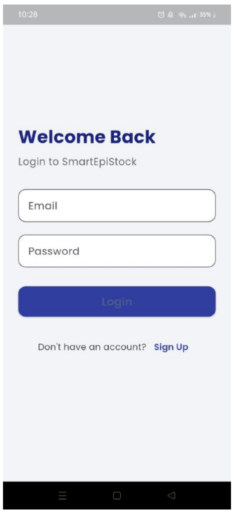

Figure 2.17: users who already have an account on the SmartEpiStock app

image-based grain classification, semantic ontologies for knowledge representation and reasoning, and IoT-based sensing for real-time environmental monitoring, the system is designed to provide a comprehensive and adaptive approach to storage management.

The combination of MobileNetV3 for efficient image classification, a domain-specific ontology enriched with SWRL rules for decision support, and a user-centered mobile application ensures that the system meets both technical performance and practical usability requirements. The presented architecture enables continuous data acquisition, intelligent interpretation of heterogeneous data sources, and timely generation of alerts

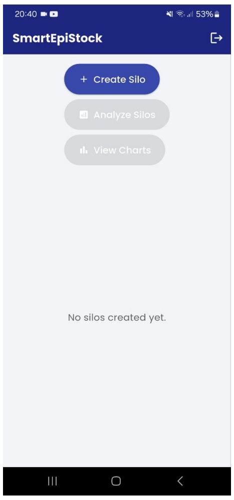

Figure 2.18: Home screen displayed when no silos have been created yet. Only the "Create Silo" button is active; other options are disabled.

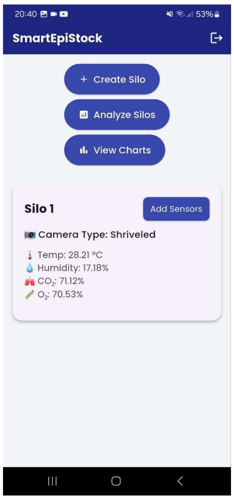

Figure 2.19: after the first silo has been created.

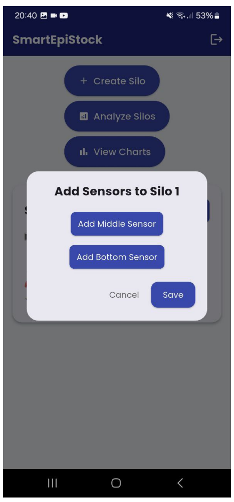

Figure 2.20: Interface allowing the user to add a sensor to the middle or bottom of the silo, with Save and Cancel buttons.

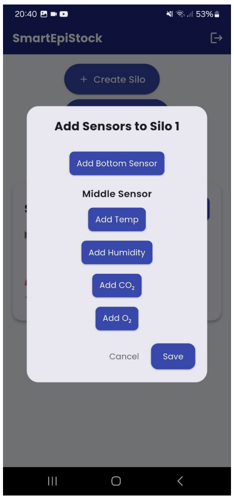

Figure 2.21: Advanced sensor configuration screen with options to add temperature, humidity, CO, and O sensors in the middle or bottom of the silo.

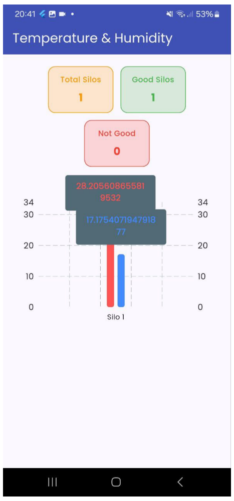

Figure 2.22: Temperature and humidity monitoring interface for storage silos.

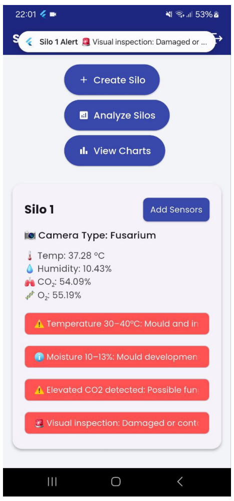

Figure 2.23: Detailed alert view for Silo 1

Conclusion and Perspectives

This Master thesis presented the design and implementation of SmartEpiStock, an intelligent system for real-time monitoring and management of wheat grain storage conditions. Conducted within the broader context of digital transformation in agriculture, the project sought to address persistent challenges related to post-harvest losses, environmental variability, and the lack of responsive monitoring tools in silo management.

To meet these challenges, we proposed a hybrid approach combining three complementary technologies: Internet of Things (IoT) for environmental data acquisition, Deep Learning (MobileNetV3-Large) for visual classification of grain quality, and Semantic ontologies enriched with SWRL rules for advanced reasoning and alert generation.

The proposed architecture supports continuous monitoring of key parameters and leverages AI to detect anomalies, and the integration of ontological reasoning. The development of a user-friendly mobile and desktop application ensures accessibility for end users, particularly silo operators.

The evaluation of the system demonstrated both its technical feasibility and its potential to significantly enhance storage practices. The deep learning model achieved strong classification performance, while the ontology enabled flexible rule based inference. These components form a reliable, modular, and scalable solution for intelligent grain storage management.

Building on this foundation, several directions can be explored to extend and enhance the SmartEpiStock:

- **Integration of additional sensors:** Incorporating gas sensors (e.g., ethylene, ammonia), vibration detectors, or insect movement trackers could further enrich the environmental understanding and risk detection capabilities.

- **Improvement of AI models:** Training the deep learning model on a larger, more diverse dataset including images from different insects improve generalization and robustness.

- **Scalability to other grain types:** The architecture could be adapted for monitoring other grain types such as maize or barley, by adjusting the ontology and retraining classification models.

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Annexe 01: Used Software tools

Development environment

Annaconda

Anaconda is an open-source distribution of the Python and R programming languages specifically designed for data science, with the aim of simplifying package management and deployment. It uses the Conda package manager to handle package versions and manage environments, ensuring that installations do not conflict with existing packages or frameworks. The distribution comes with over 250 pre-installed packages and provides access to more than 7,500 additional open-source packages from both PyPI and Conda repositories.

Anaconda also includes a graphical interface called Anaconda Navigator, which offers a user-friendly alternative to the command line. With Anaconda Navigator, users can easily launch applications, manage packages, configure environments, and access channels—all without writing terminal commands. It allows users to search for packages, install them into specific environments, run them, and ensure they are up to date [91].

Jupyter

It is an interactive web-based development environment for notebooks, code, and data. Its flexible interface makes it easy to set up and manage workflows in fields such as data science, scientific computing, computational journalism, and machine learning. Thanks to its modular architecture, it is possible to add extensions that enhance its functionality [92].

Programming language

Python

Python is a powerful and flexible programming language that is extensively used across multiple domains, including web development, data analysis, machine learning, and scientific computing. The most recent version, Python 3, introduces enhanced syntax, better Unicode support, improved memory management, and overall performance gains. Maintained by the Python Software Foundation, Python benefits from a vast ecosystem of libraries and frameworks tailored to a wide range of applications [93].

Used Libraries

TensorFlow

TensorFlow is an open-source software library developed by the Google Brain team for artificial intelligence and machine learning applications. Although it supports a broad spectrum of machine learning tasks, its primary use lies in the training and inference of neural networks. Since its public release under the Apache License 2.0 in 2015, TensorFlow has become one of the most widely adopted deep learning frameworks, alongside alternatives such as PyTorch.

A major revision, TensorFlow 2.0, was launched in September 2019, introducing a more user-friendly and consistent API. TensorFlow supports multiple programming languages, including Python, JavaScript, C++, and Java, making it a flexible tool widely used across both research and industry domains [94].

Keras

Keras is a high-level deep learning library written in Python, designed to simplify the creation and training of neural networks. Operating as an interface rather than a standalone framework, Keras runs on top of backends such as TensorFlow. It abstracts away the complexity of tensor operations, shapes, and mathematical calculations, allowing developers to build and experiment with deep learning models more intuitively. Thanks to its modular architecture and user-friendly syntax, Keras is particularly suitable for beginners, while still being powerful enough for advanced applications [95].

Scikit-learn (sklearn)

is a Python library that provides a comprehensive selection of machine learning algorithms for both supervised and unsupervised learning tasks. Built on top of foundational libraries like NumPy, SciPy, and Matplotlib, it offers a user-friendly interface for data handling. Scikit-learn supports tasks such as classification, regression, clustering, and dimensionality reduction, along with tools for data preprocessing, model selection, and evaluation. Its simplicity, flexibility, and scalability have made it widely adopted in both academic research and industry. Moreover, its extensive documentation and active community make it a valuable resource for those working in machine learning [96].

Matplotlib

is a Python library designed for creating 2D visualizations, including static, animated, and interactive plots. It is extensively used in scientific computing for data visualization and exploration. With a rich set of plotting capabilities and a high degree of customization, Matplotlib allows users to build detailed and sophisticated visual representations of data with ease. Its compatibility with various Python libraries and frameworks enhances its flexibility for data visualization across different contexts [97] .

Numpy

NumPy is a foundational Python library for numerical computing. It provides support for efficient manipulation of large multi-dimensional arrays and matrices, along with a vast collection of mathematical functions. NumPy's array-oriented computing enables vectorized operations, which significantly enhance performance compared to native Python data structures. It plays a critical role in fields such as scientific research, engineering, and data science. Additionally, NumPy includes modules for linear algebra, statistical operations, Fourier transforms, and random number generation, and it serves as the backbone for many other scientific libraries in Python [98].

Owlready2

Owlready2 is a Python library designed for ontology-oriented programming. It enables users to load, manipulate, and save OWL 2.0 ontologies as native Python objects, while also supporting reasoning capabilities through the integrated HermiT reasoner. Unlike traditional Java-based APIs, Owlready2 provides seamless and transparent access to OWL ontologies directly within Python. Version 2 of Owlready introduces an optimized triplestore/quadstore built on SQLite3, offering improvements in both performance and memory efficiency. Unlike its predecessor, Owlready2 is capable of handling large-scale ontologies. Additionally, it includes support for accessing UMLS and various medical terminologies via the built-in PyMedTermino2 module [99].

Annexe 02: Annexe StartUp

Project Presentation

The project idea (proposed solution)

- The business area of the project is smart agriculture, with a focus on the automated and optimized management of wheat grain storage.
- The idea originated from recognizing the significant losses in quality and quantity that often occur during grain storage due to poor environmental control (e.g., humidity, temperature, mold, insect infestations). Traditional monitoring methods are often manual, infrequent, and inefficient.
- The project proposes the development of an intelligent stock management system that integrates artificial intelligence (AI) ,Internet of Things (IoT) sensors, camera-based monitoring to analyze and control storage conditions in real time.
- IoT sensors will continuously measure key environmental parameters such as temperature, humidity, and CO2 levels. Simultaneously, cameras installed in silos will capture images that are automatically analyzed to detect visual anomalies like mold growth, insect presence, or spoilage.
- The system will collect data and trigger intelligent alerts and recommendations. An application mobile will allow managers to visualize real-time data, receive warnings.

The Proposed Values

- The system significantly reduces storage losses through continuous, automated monitoring of both environmental and visual conditions.
- It improves the quality and safety of wheat grain storage by detecting risks early, including heat buildup, mold development, excessive humidity, and biological threats—thanks to the combination of sensor data and image-based artificial intelligence analysis.
- It enhances traceability and food safety.
- It enables cost savings by reducing unnecessary manual inspections and supporting targeted corrective actions only when needed.
- The system features a modular, scalable architecture that can be easily integrated into various agricultural storage facilities, with plug-and-play installation and future-ready updates.
- Ultimately, this solution drives the transition toward smart, sustainable agriculture, empowering decision-makers with real-time, data-driven insights.

Work team

Harizi Rana
Bouacida Imane
Djakhdjakha Lynda

The project's objectives

– **Short Term:** Deploy an MVP in 2–3 grain storage units in Algeria and collect performance data.

– **Medium Term:** Expand to more agricultural regions and integrate with cooperatives and private silos.

– **Long Term:** Become the go-to AI monitoring solution for smart agriculture in North Africa and the Middle East.

Project completion schedule

Phase	1m	2m	3m	4m	5m	6m
Preliminary Studies	*	*				
Service Development		*	*	*		
Testing & Launch	*					
Marketing & Promotion					*	*

Table 2.4: Project Completion Schedule

Innovative Aspects

– This project stands out for several reasons: It combines three advanced technologies: IoT (sensors for temperature, humidity, CO2,O2 and Camera), Ontology (a smart knowledge-based system to understand concepts), and AI that classifies grain conditions using images.

– The system can operate autonomously: collecting data, analyzing it intelligently, and sending alerts in case of risks (e.g., mold, humidity anomalies).

– It offers a mobile application for real-time monitoring.

– It is designed to be adapted to local needs, including resource-limited environments.

– It replaces traditional manual tracking methods with a modern, automated, and intelligent mobile application.

– It helps reduce losses and ensures better storage decision-making.

Strategic Market Analysis

a. Target Market:

– Agricultural cooperatives and cereal storage centers.

– Large-scale farmers and silo owners.

– Agritech companies and startups.

– Public institutions working in food security.

b. Competitive Analysis:

There are some basic systems that use IoT to monitor temperature or humidity. However, they lack intelligence, no image classification, no automated decision-making, and no ontology.

Traditional methods rely on manual inspection, which is neither scalable nor reliable.

Our system stands out because it is:

– Affordable (can be implemented with low-cost sensors).

– Autonomous (makes decisions without human intervention).

– Domain-specific (tailored for wheat grain storage).

c. Marketing Strategy

– Awareness campaigns about AI and smart monitoring benefits in agriculture.

– Pilot deployments in targeted storage units with published results to build trust.

– Collaboration with agricultural ministries, cooperatives, and farmer organizations.

– Offering starter kits at reduced cost for early adopters (freemium model or subsidy-based).

– Participation in agricultural expos, tech fairs, and agritech webinars.

– Online presence via website, case studies, demo videos, and expert articles.

d. Communication Strategy

– Demonstrations in agricultural events and exhibitions.

– Partnerships with agricultural cooperatives and incubators.

– Online marketing (social media, website, and agritech platforms).

– Publications and presentations in academic or professional settings.

Production and Organization Plan

The Production Process

- **Partnership Development:** Collaboration with agricultural cooperatives, AI and semantic research institutions, IoT sensor suppliers, equipment manufacturers, and public institutions.

- **System Development:**
  - IoT module integration (temperature, humidity, CO_2, motion).
  - Wheat grain classification.

  - Ontology-based reasoning with rules.
  - Mobile app development with alert system and dashboards.

- **Testing and Deployment:** Pilot deployment in storage silos, real-world testing, and evaluation of model accuracy and alert performance.

- **Agro-Digital Launch:** System launch through agricultural fairs, cooperatives, and institutional partnerships.

Supply

- IoT sensor and microcontroller suppliers (e.g., DHT22, MQ2, PIR, ESP32).
- Agricultural equipment manufacturers for integration.
- Local server components and storage systems.
- Partner universities for validation and support.

Employees

The project is expected to create approximately 40 to 50 job opportunities, including:

- artificial intilligence developers.
- IoT engineers and embedded systems specialists.
- Ontology and semantic web engineers.
- Mobile and web developers.
- Field technicians and deployment staff.
- Agronomists and product advisors.
- Technical support and user training teams.

Special Discussion

Strategic partnerships are essential with:

- Agricultural institutions for scalability and support.
- Sensor and equipment manufacturers for cost-effective integration.
- Research centers and universities for knowledge and validation.

Financial Plan

Costs and Charges

The identification of all necessary costs and investments is crucial to ensure the success and sustainability of the project. These include initial, operational, recurring, and additional strategic expenses.

A) Initial Costs

Infrastructure:

- Setting up or leasing office spaces for development and administration.
- Installation of local servers, computers, and secured network infrastructure.
- Implementation of safety systems: access control, fire protection, UPS devices.

Equipment:

- **Sensors:** Temperature and humidity (DHT22), gas (MQ2), motion (PIR), CO and O sensors.
- **Microcontrollers:** ESP32 or Arduino boards for sensor integration and data collection.
- **Computers and Workstations:** For developers, analysts, and system users.
- **Networking Equipment:** Routers, switches, and IoT communication modules.
- **Software Licenses:** TensorFlow, Protégé, Android Studio, and development IDEs.
- **Office Supplies and Furniture:** Desks, chairs, and consumables (pens, notebooks, etc.).

Technology:

- **Ontology Tools:** Semantic web frameworks using OWL, SWRL, owlready2.
- **Data Management Systems:** Secure databases and data warehouses.
- **User Interfaces:** Mobile/web interfaces for sensor monitoring and alerts.
- **AI Modules:** Image classification (e.g. mold detection).
- **Dashboards and Reports:** Visual tools to present system metrics and alerts.

B) Operational Costs

Personnel:

- Salaries for developers, AI engineers, ontology experts, technicians, and support staff.
- Consultant fees (AI, IoT, agriculture).
- Ongoing training on smart farming, AI, and semantic web technologies.

Logistics and Services:

- Software subscriptions for development and analytics tools.
- Acquisition of datasets for AI training (sensor readings, images, environmental data).

Marketing and Customer Support:

- Marketing campaigns: online advertising, awareness campaigns, demo videos.
- Support systems for assisting users and responding to technical issues.

C) Other Costs

- Insurance (hardware, cyber liability).
- Legal compliance (data privacy, licensing).
- Regulatory fees and permits for hardware and software deployment.

D) Recurring Costs

- Software license renewal.
- Maintenance and update of sensors and equipment.
- Updating AI models and the mobile/web platform.

Financing Methods and Sources

A) Internal Financing

- Company's own capital and savings.
- Reinvested profits from previous business activities.

B) External Financing

Bank Loans:

- Long-term loans for equipment and infrastructure.
- Credit lines for covering operational costs.

Investors:

- Search for investors focused on agri-tech, AI, and IoT.

- Form partnerships with cooperatives or tech entrepreneurs.
- Explore monetization strategies for mass adoption of the platform.

Subsidies and Grants:

- Government support programs for digital agriculture.
- International funding (FAO, World Bank, EU, etc.).
- Participation in incubators and accelerators for AI or smart farming.

Crowdfunding:

- Launch of public fundraising campaigns (Kickstarter, Indiegogo, etc.).

Financing Reimbursement Strategy

Repayment Schedule:

- Clear repayment plan with timelines, amounts, interest rates, and grace periods.

Cash Flow Forecasting:

- Monitor monthly income and expenses to ensure financial stability.
- Adjust expenses as needed to maintain positive cash flow.
- Include a buffer for unforeseen costs.

Reimbursement Plan

Date	Amount	Financing Type	Due Date	Remaining Balance
2025-07-01	1 000 000 DZD	Initial Investment	N/A	1 000 000 DZD
2025-08-15	500 000 DZD	Sensors & Equipment	N/A	500 000 DZD
2025-09-30	750 000 DZD	Deployment & Testing	N/A	1 250 000 DZD
2025-10-15	300 000 DZD	Software Licenses	N/A	950 000 DZD
2025-11-30	400 000 DZD	Technician Salaries	N/A	550 000 DZD

Table 2.5: Payment Table – Smart Grain Storage Monitoring Project (2025)

Business Model Canvas

Designed for:

Designed by:

Date:

Version:

Key Partners

1. Providers of smart IoT sensors (temperature, humidity, CO_2, etc.) for real-time silo monitoring.
2. Universities and research institutions specialized in AI and semantic technologies for AI research, ontology design, and validation.
3. Agricultural cooperatives and silo managers for : testing and adopting the solution.
4. Agricultural equipment manufacturers for hardware integration.
5. Governmental institutions in the agricultural sector for support and scale-up for : regulatory support, scale-up programs, and funding.

Key Activities

1. Data collection using IoT sensors.
2. Image analysis and classification using deep learning (MobileNetV3).
3. Intelligent reasoning through ontology and SWRL rules.
4. Alert generation and recommendations via a mobile app.
5. Maintenance and updates of models and the knowledge base.
6. User onboarding and training for optimal system adoption.

Key Resources

1. Smart sensors and embedded systems.
2. AI-based image classification model.
3. Custom ontology for wheat storage.
4. Mobile application .
5. Technical team for deployment and support.

Value Propositions

1. A smart system for real-time monitoring of wheat storage conditions.
2. Early detection of risks (humidity, fermentation, insect infestation).
3. Reduction of post-harvest losses and improved grain quality.
4. Easy-to-use app with instant alerts to responsible parties.
5. Decision support powered by domain-specific rules.
6. Compliance with food safety and storage regulations.
7.

Customer Relationships

1. Onboarding support (installation and setup).
2. Ongoing technical assistance.
3. Customized alerts based on storage profiles.
4. Simple interface with optional access to expert support.

Channels

1. Direct sales through agricultural cooperatives.
2. Online platform with local installation partners.
3. Downloadable mobile app (Android).
4. Demonstrations at agricultural fairs and events.

Customer Segments

1. Silo managers and agricultural cooperatives.
2. Farmers with their own storage facilities.
3. Public institutions involved in food safety and storage.
4. Logistics and agricultural storage companies.

1. **Cost Structure**
2. Hardware manufacturing and sensor costs.
3. Software development (AI, ontology, app).
4. User training and onboarding support.
5. Technical support and system maintenance.
6. Marketing and demonstration campaigns.

Revenue Streams

1. Sale of hardware kits (sensors + controller).
2. Monthly subscription for platform access and smart alerts (2000DZ).
3. Custom packages for large-scale farms or industrial silos.
4. Potential partnerships or subsidies for rural deployment.