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Desenho e Desenvolvimento de um Sistema de Gestão de Inventário Inteligente para Objectos Perdidos

Design and Development of an Intelligent Inventory Management System for Lost Items

DOCUMENTO PROVISÓRIO

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Design and Development of an Intelligent Inventory Management System for Lost Items

Dissertação apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Engenharia Informática, realizada sob a orientação científica do Doutor Eurico Farinha Pedrosa, Professor associado do Departamento de Eletrónica, Telecomunicações e Informática da Universidade de Aveiro, do Doutor Mario Luís Pinto Antunes, Professor associado do Departamento de Eletrónica, Telecomunicações e Informática da Universidade de Aveiro.

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acknowledgement of use of AI tools

Recognition of the use of generative Artificial Intelligence technologies and tools, software and other support tools.

I acknowledge the use of Grammarly (Grammarly, https://www.grammarly.com/) to improve and correct some sentences and paragraphs, pontuation and vocabulary. I acknowledge the use of ChatGPT-3.5 to improve the overall deliver of this Dissertation document.

Contents

List of Figures

List of Tables

Glossary

ACDM Architecture-Centric Development Method

AI Artificial Intelligence

API Application Programming Interface

BERT Bidirectional Encoder Representations from Transformers

CLIP Contrastive Language-Image Pre-training

CNN Convolutional Neural Network

CV Computer Vision

DL Deep Learning

GDPR General Data Protection Regulation

GPT Generative Pre-trained Transformer

IMS Inventory Management System

LLaVA Large Language and Vision Assistant

LF Lost-and-Found

LFMS Lost-And-Found Management System

LLM Large Language Model

ML Machine Learning

MVP Minimum Viable Product

NLG Natural Language Generation

NLP Natural Language Processing

NLU Natural Language Understanding

RFID Radio-Frequency Identification

ResNet Residual Neural Network

QR Quick Response

SLR Systematic Literature Review

UI User Interface

UX User Experience

YOLO You Only Look Once

CHAPTER 1

Introduction

"We never discover the value of things till we have lost them"
- Dinah Maria Craik, A Life For A Life (1859)

1.1 Context

The loss of personal items is a common situation that affects individuals in various contexts, from public spaces such as airports, universities and shopping centres [1], [2] to private institutions such as schools, companies and factories. On average, people misplace or completely lose up to nine items each week, with common culprits including mobile phones, keys, and sunglasses [3]. This distraction costs individuals from 15 to 50 minutes each day spent searching for these misplaced items [3], [4]. Over an average of 60 years of stated adult life, that implies approximately at least a total of 3680 hours (153,3 days) and 200 000 items misplaced or wholly lost [5]. Adding to this issue, studies have revealed that the time spent searching for lost items can lead to financial losses that feel akin to literally throwing money away. The cumulative effect of these lost hours not only frustrates individuals but also impacts their financial well-being, a stark reminder of how daily distractions can drain both time and resources. These effects, when aggregated over long periods, also have alarming outcomes. The same studies also reveal a staggering annual waste of approximately $177 billion dollars made by United State citizens [6] due to time spent searching for lost or misplaced items [5], which represents a figure that highlights a significant drain on productivity.

Traditionally, manually managing lost property has long been plagued by inefficiencies that disadvantage its corresponding stakeholders, i.e. the administrators and the individuals, both seeking to deliver and recover the lost belongings [7]. In most cases, the process relies heavily on manual efforts, requiring staff to record, store and track items using rudimentary tools such as paper records or basic spreadsheets. Others resort to simple and outdated Inventory Management Systems (IMSs) that are not designed to handle the complexities of lost property management [8]. This labour-intensive approach is time-consuming and prone to human error, leading to lost items, inaccurate records and miscommunication between departments or stakeholders [7], [8]. Additionally, most of the designated staff responsible for handling these tasks is rarely compensated or formally recognised for this additional responsibility. These employees are typically expected to manage lost items alongside their regular workload without extra pay, training, or resources [8]. They are tasked with organising found objects, responding to enquiries and ensuring that the rightful owners are identified, often with little or no support from automated or systematic processes, that divert attention from their core responsibilities and also foster frustration as they navigate an unsustainable workflow.

On the other hand, individuals searching for lost objects face many significant challenges. The lack of a standardised or intuitive system means they have to rely on guesswork or luck to recover their belongings. The stress is even more significant when they do not know where to start their search or if their lost object has already been found. It is the so-called "lost-and-found" effect, described by Gärling and Hansla [9] , explaining the stressful mental process of over-valuing and prioritising the recovery of a missing item. The absence of transparent communication channels [8] or efficient recovery mechanisms further enhances this effect.

Complementing the ineffectiveness, the risks associated with poorly managed lost items are substantial. Without secure processes, lost objects are vulnerable to theft or unauthorised access [10]. Identity theft and forgery become tangible threats when personal or sensitive belongings, such as identification documents or personal electronic devices, fall into the wrong hands [11]. In addition, the public disclosure of personal information associated with lost property has become a concern that has not yet been the subject of a standardised solution [11]. Furthermore, mismanagement can lead to legal complications, especially if disputes arise over lost objects that are improperly registered or not returned to the rightful owner. A prevalent issue with lost property platforms is the failure to establish a robust sense of trust among users [11]. Specifically, there is often a lack of reliable assurance between the owner of the lost item and the finder. This vulnerability can lead to dishonest behaviour, including fraudulent claims or requests.

From an organisational point of view, even though some institutions provide designated LF collection points [10], they also run the risk of damaging their reputation, potentially being held accountable and damaging relations with the communities they serve.

In a world where technology effortlessly simplifies our daily tasks, it is striking that we lack effective technological solutions for locating our physical belongings. This discrepancy highlights a critical gap in our everyday lives, underscoring the urgent need for innovative tools that can help us find our lost possessions efficiently.

1.2 Motivation

Since managing lost objects still represents a common challenge, creating a more efficient system to solve this problem can ease the burden among users and the community. With more efficient Lost-And-Found Management System (LFMS), manual processes that are currently riddled with inefficiencies can be completely redesigned. Institutions can not only optimise recovery processes but also strengthen their commitment to user satisfaction, thus improving community relations and institutional reputation.

Emerging technologies such as Artificial Intelligence (AI), Natural Language Processing (NLP) and the increasing training and use of Large Language Models (LLMs) offer unprecedented opportunities to address these challenges. AI can facilitate the identification and categorisation of lost objects, while NLP enables the use of users' interactions, such as searches and conversations, to extract relevant data [3], which can then be used in the user's best interest. In recent years, the advent of **dp!** (**dp!**) has revolutionised the performance of various visual tasks, leading to significant advancements in areas such as image classification [12]. These improvements are not limited to mere accuracy; they encompass enhanced efficiency in processing large datasets, the ability to recognise intricate patterns, and the capability to generalise across diverse scenarios.

This dissertation is motivated by the potential of these technologies to innovate in an area that remains barely explored, aiming to transform the LF management into an efficient, secure and user-friendly experience. The integration of these technologies can redefine the standards of lost objects' recovery and management, resolving inefficiencies and building trust among stakeholders. Beyond merely improving operational processes, a reimagined system for managing lost property must also emphasise community integration. By enabling direct communication between finders and owners, supported by platforms for community-based reporting, the solution can minimise reliance on intermediaries and streamline the recovery process. The community-oriented approach proposed by Guinard *et al.* [8] not only fosters trust among stakeholders but also encourages a culture of shared responsibility and collaboration, empowering users to take an active role in solving LF challenges.

1.3 Objectives

This research seeks to establish a straightforward framework for addressing the inefficiencies in the management of LF property by defining specific and measurable objectives. A primary goal is to design and develop an intelligent IMS specialised for LF, by exploring the application and capabilities of AI and NLP for automating the identification, categorisation, and recommendation of lost items, aiming to reduce manual workload and effectively complete the LF cycle of items. Another objective is to prioritise usability by ensuring that the proposed solution accommodates individuals with varying levels of technological proficiency, which involves examining design strategies that promote accessibility and simplify interactions, fostering a more inclusive approach. The last objective is to include community-oriented features, which may encourage community engagement, emphasising on fostering direct communication between users. This engagement indicates that the level of user interactions will highly modify the user experience.

The research aims to employ iterative testing and validation in both controlled and real-world settings, including evaluating the system under diverse conditions. Consequentially, it implies the need to implement record-keeping and observability methods to generate actionable insights, enabling continuous improvement of the solution.

The proposed research can be conducted in four key stages, which align with a logical progression from understanding the problem to delivering a robust, focusing on different aspects of design and development.

1. Study the State-of-the-Art: Review existing i) Lost-And-Found Management System, ii) in-production solutions, iii) available and recommended technologies and iv) best practices and optimal approaches;
2. Design the structure of the system by defining its architecture, features and workflows;
3. Create the main system components, including all the planned features;
4. Test the system in a real-world and controlled environment;
5. Finalise and document the results for academic and practical use.

1.4 Dissertation Outline

This dissertation is structured into multiple chapters, each building upon the previous to provide a comprehensive understanding of the research and its outcomes. The document begins with this introductory chapter, Chapter 1, that offers background information, including the core problem being addressed, the motivation for this research, and the objectives associated with the proposed solution.

Following this, Chapter 2 examines the state of the art and explores topics such as traditional and modern LFMSs; Computer Vision (CV), directly connected with the advances on AI; NLP and the use of LLMs to perform Natural Language Understanding (NLU) tasks; and many others.

Chapter 3 focuses on explaining the first design decisions for the platform, namely the architectural design that resulted in the notional architecture.

The following chapters are expected to cover the development of a proposed Minimum Viable Product (MVP), the integration with the intelligent technologies, the results from the system's real-world testing, the system's quality assessment and the conclusions driven from this dissertation.

CHAPTER 2

State of Art

2.1 Manually Managing Lost-and-Found Items

2.1.1 Traditional Management Systems

Traditional LFMSs typically relied on manual processes to log and manage items, sometimes papers or books and, in a few cases, spreadsheets [13]. The fundamental components included physical logs, where details of found items - such as descriptions, location, and date of discovery - were recorded by staff or custodians.

Often, the responsibility of maintaining these records fell to a designated individual or department. Items were categorised and stored in a secure area, with the hope that owners would reclaim them. Matching found items to reported losses was a manual process, requiring significant time and effort [13]. Descriptions provided by claimants were cross-referenced with recorded details to determine ownership. In some cases, rudimentary tagging systems were used to label items, aiding the identification process.

In environments like universities or corporate campuses, basic digital tools such as spreadsheets were usually introduced to track items. However, the overall workflow remained heavily dependent on manual oversight. Community bulletin boards, notices, or word-of-mouth were also standard methods to inform individuals about found items.

Despite their simplicity, these systems played a critical role in facilitating the return of lost belongings in the pre-digital era [14]. They fostered a sense of trust and collaboration within communities, relying on the goodwill and honesty of both finders and administrators. The traditional systems established the groundwork for modern approaches, providing valuable insights into the challenges and requirements of effective LF management.

Despite the previously detailed inefficiencies of such systems, there are still those who would find these manual workflows to be more trustworthy. For some, the human element brings a level of accountability and understanding that automated systems cannot replicate. Manual processes allow for subjective judgment, which can be beneficial in complex scenarios where nuance is required. The tactile nature of handling paper documents or physical records fosters a sense of security and reliability. Moreover, people who have had negative experiences with technology might prefer traditional methods, viewing them as more stable and less prone to glitches or failures.

2.1.2 Obstacles in Traditional Systems

While traditional LFMSs have historically served their purpose in smaller or less demanding contexts, they face significant challenges when scaled to handle larger volumes of items or more complex environments [14]. The scalability of such systems is inherently constrained by their reliance on manual processes and both limited technological integration and automation.

A key obstacle is the dependency on human effort. As the number of items increases, so does the burden on staff, leading to delays, errors, and inefficiencies. In high-traffic environments, the sheer volume of items can quickly overwhelm even the most organised traditional systems. Without automation, processing and resolving claims becomes a time-intensive task, reducing the workflow's overall effectiveness.

Another barrier to scaling is the lack of centralised data management. In traditional systems, records are often siloed, with each location or department maintaining its logs. Especially in larger organisations or distributed campuses, the absence of a unified database also impedes efficient reporting and analysis of trends, such as identifying frequent loss locations or categories of items.

Communication between stakeholders presents further challenges. Traditional systems often lack any mechanisms for notifying individuals about found items or updating claimants on the status of their reports, resulting in inefficiencies and frustrations, particularly in large-scale operations where the number of inquiries can be substantial.

Finally, the security of manual systems poses significant concerns. As the volume of items increases, the risk of theft, loss, or unauthorised access also rises. Inadequate labelling and verification processes can lead to disputes or errors in returning items to their rightful owners, further eroding trust in the system.

2.2 Inventory Management Systems

IMSs are tools designed to manage and track inventory levels across various domains. These systems enable organisations to streamline their operations, reduce costs, and enhance customer satisfaction by ensuring the availability of necessary items at the right time and place [15]. An IMS employs methodologies to identify and classify inventory items based deatails like quantity, volume, value or variability, optimising inventory performance through targeted strategies [15].

Fundamentally, an IMS aims to address some challenges, such as maintaining inventory levels, reducing holding costs, mitigating risks and many others associated with collections and stocks. Techniques like safety stock determination and lot-sizing methods have been widely adopted [16]. Such systems have historically evolved to incorporate some technological advancements, obtaining the capability to predict, plan, and execute inventory operations Automatically and effectively [17].

While conventional IMSs primarily focus on physical products, their underlying principles can be effectively applied to tracking and managing LF items. This intersection becomes particularly relevant in environments where the inventory (in this case, lost items) exhibits variability in value, volume, and retrieval demand. Inventory management principles, such as classification and optimisation, can be applied to LFMSs to streamline processes and enhance user experiences. For instance, using the classification method mentioned before, in a LFMS, items could be categorised using an adapted ABC-XYZ[1]framework that enables prioritisation of storage, retrieval, and notification efforts [18]. The Table 2.1 illustrates a potential result of that association:

Table 2.1: Classification of LF items using the ABC-XYZ framework

Class	Value	Volume	Retrieval Demand	Examples
A-X	High	Low	Consistent	Electronic devices, jewellery
B-Y	Moderate	Moderate	Fluctuating	Wallets, bags, clothing
C-Z	Low	High	Irregular	Umbrellas, stationery

The insights from Plinere and Borisov [19] further support the integration of these methodologies into LFMSs. Their case study emphasises the significance of structured inventory management practices for improving operational efficiency. For instance, high-priority items, such as class A-X items, can benefit from focused attention and expedited claim processes, ensuring user satisfaction while reducing storage costs. Furthermore, their findings highlight the value of predictive analytics in addressing slow-moving or stagnant inventory, matching to unclaimed items [19]. Technological integration, as illustrated in the case study, offers another avenue for improvement. The use of Radio-Frequency Identification (RFID) and Quick Response (QR) codes in conventional inventory systems ensures accurate tracking and categorisation of items [19], [20]. Moreover, the adoption of resource planning principles, such as imposing a centralised warehouse, would improve transparency and decision-making, possibly enabling a seamless synchronisation of data across departments. Lastly, the Plinere and Borisov [19] study underlines the importance of standardisation in inventory management policies, e.g., uniform intake procedures, categorisation standards, and clear guidelines for item disposition.

Adapting IMSs for LF management would definitely address some unique challenges [15]. Unlike traditional inventory, lost items often have sentimental value or urgent retrieval needs, requiring the system to incorporate real-time tracking and user-friendly interfaces. Moreover, integrating predictive analytics, commonly used in IMSs for forecasting demand, would be leveraged to anticipate peak periods of item loss or retrieval, e.g., events or seasons that may influence the volume and types of items lost, allowing proactive resource allocation [16].

Building on these foundational principles, open-source IMSs have evolved to address specific needs, blending traditional methodologies with modern technologies to enhance

[1]Suryaputri Z. and Gabriel, D.S. and Nurcahyo R., Integration of ABC-XYZ Analysis in Inventory Management Optimization: A Case Study in the Health Industry, Proceedings of the International Conference on Industrial Engineering and Operations Management, 2020, `https://ieomsociety.org/proceedings/2022nigeria/70.pdf`

their adaptability and utility across domains. Odoo Inventory[2], for instance, exemplifies this progression by integrating inventory management with enterprise-level tools like sales and customer relationship management. Its multi-warehouse support and barcode scanning capabilities make it a robust solution for medium to large enterprises. In contrast, Snipe-IT[3] focuses on a narrower domain (asset tracking), offering a well-designed interface for managing fixed assets, albeit without features like demand forecasting or multi-warehouse management. Moving further into specialised territories, InvenTree[4] demonstrates how inventory systems can cater to engineering and manufacturing by providing tools for managing parts and components through hierarchical structures and batch tracking. However, it lacks the scalability offered by integration with other systems. Meanwhile, SkuNexus[5] exemplifies the pivot toward e-commerce needs, combining advanced reporting, omnichannel order fulfilment, and process automation for complex operations, though its configurability demands significant effort during implementation. For small-scale, niche applications, PartKeepr[6] offers essential inventory management tools, such as batch tracking and stock alerts, tailored to managing electronic components but without the scalability or advanced features needed for more extensive operations.

The following Table 2.2 summarises the key features of these systems, highlighting their areas of strength and limitations:

Table 2.2: Summarised comparison of open source Inventory Management System by features

IMS	MWS	BI	DF	BT	ERPI	UFI
Odoo	Yes	Yes	Yes	Yes	Yes	Yes
Snipe-IT	No	No	No	No	No	Yes
InvenTree	No	Yes	No	Yes	No	Yes
SkuNexus	Yes	Yes	Yes	Yes	Yes	No
PartKeepr	No	Yes	No	Yes	No	No

MWS - Multi-Warehouse Support, BI - Barcode Integration, DF - Demand Forecasting, BT - Batch Tracking, ERPI - ERP Integration, UFI - User-Friendly Interface.

2.3 Systematic Literature Review

2.3.1 Research Question and Methods

LF management has historically presented numerous challenges across both public and private sectors, as highlighted in a wealth of academic articles and studies [3]. To address previously mentioned persistent issues and uncover effective solutions, a rigorous Systematic Literature Review (SLR) was undertaken, focusing specifically on innovations, challenges, and best practices in the realm of intelligent lost property management. The review was designed

[2] `https://www.odoo.com/app/inventory`
[3] `https://snipeitapp.com/demo`
[4] `https://inventree.org/`
[5] `https://skunexus.com`
[6] `https://partkeepr.org/`

with a methodological rigour that adheres to the PRISMA 2020 guidelines [21], ensuring that every aspect of the research was conducted with the highest standards of integrity and transparency. By synthesising the latest uncovered findings, the SLR offers not only a comprehensive understanding of the current landscape but also valiable insights that can inform the design of a LFMS system. The SLR later resulted in the production of a document directly aligned with this dissertation's scope, named *"Designing an Intelligent Solution for Lost Property Management: A Systematic Review"*.

The review sought to answer the central research question *"How can intelligent technologies enhance the efficiency and user experience of lost property management systems?"*, which refers to how technologies such as AI, NLP, CV and many others can provide solutions to the inefficiencies in LF management. The SLR analysed numerous articles and integrated 18 high-quality studies that demonstrated the capacity to provide new insights into the investigation area. The mentioned research question was then separated into the following three major objectives:

- Evaluating the applicability of the selected technologies;
- Examining existing challenges in implementing these technologies;
- Identifying best practices to inform the design and development of a proposed system.

The SLR employed a comprehensive four-phase approach, associated with the selected PRISMA framework. During the identification phase, academic databases such as Scopus and Web of Science were queried using targeted keywords like LF Management, IMS, AI, NLP, and LLM, resulting in an initial yield of 476 studies. These were screened for relevance through the removal of duplicates and an abstract examination. In the eligibility phase, full-text articles were meticulously assessed against predefined inclusion criteria, which focused exclusively on studies published between 2020 and 2024 that addressed acai-based solutions. Non-peer-reviewed works and studies lacking empirical validation were excluded. Additionally, to ensure the robustness of the SLR, a quality assessment framework evaluated the methodological rigour and relevance of each study. Each study was rated on its technological contributions and practical applicability. Only those scoring consistently high across all criteria were included. Ultimately, in the inclusion phase, 18 studies were selected and categorised based on the technologies employed. Figure 2.1 illustrates the PRISMA flowchart, summarising the selection process. A thematic analysis was conducted, extracting valuable results into the contributions of each technological domain.

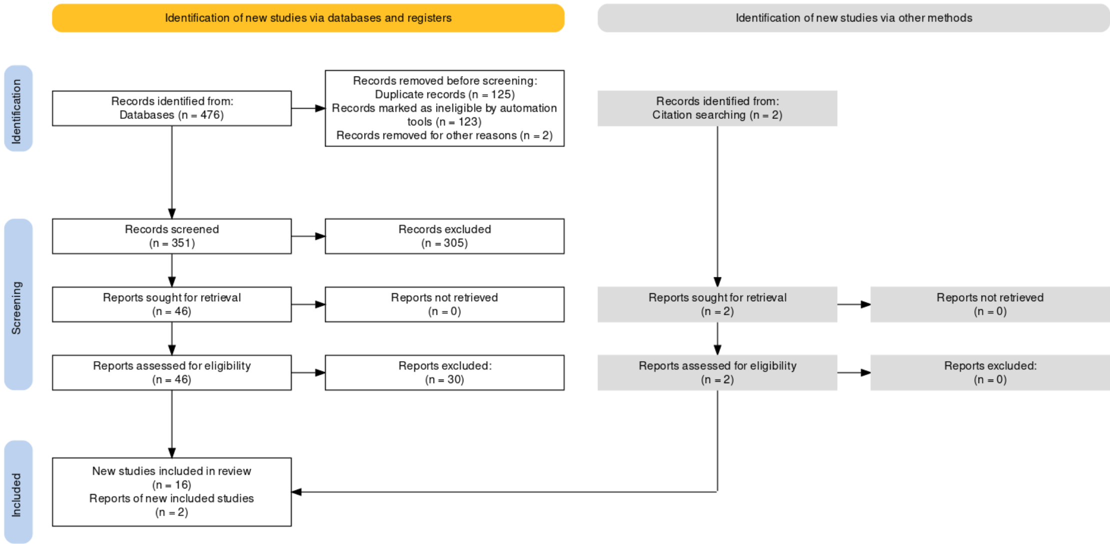

Figure 2.1: PRISMA flow diagram with a described quantity of research in each step.

2.3.2 Object Recognition and Categorisation

Object recognition and categorisation are pivotal processes in the domain of AI and CV. Object recognition involves identifying objects within an image or video and distinguishing them based on predefined features. Categorisation goes a step further by grouping identified objects into classes and/or groups of classes based on shared attributes or relationships [22]. These tasks are foundational to numerous applications, including autonomous vehicles, facial recognition, surveillance systems, and many others.

The origins of object recognition can be traced back to the early experiments in pattern recognition during the 1950s and 1960s. Early approaches relied heavily on rule-based systems, where objects were identified using manually defined features such as edges, corners, or textures. Marr [23] 's seminal work on computational vision in the 1980s introduced the concept of multi-level processing, exposing the importance of integrating both low-level (e.g., edge detection) and high-level (e.g., semantic) features. The field evolved significantly in the 1990s with the advent of statistical methods and Machine Learning (ML). Techniques like support vector machines and decision trees provided more robust frameworks for categorisation [24]. Concurrently, datasets such as MNIST[7] and ImageNet[8] emerged, enabling standardised benchmarking and driving advancements in recognition accuracy.

The evolution of object recognition and categorisation has been marked by the rise of Deep Learning (DL) in the 2010s. Convolutional Neural Networks (CNNs), such as AlexNet[9] and Residual Neural Network (ResNet), models capable of leveraging feature extraction, revolutionised this field by achieving human-like performance on challenging tasks. These models finally enabled the recognition of complex patterns and relationships in data [25], [26]. More recently, transformer-based architectures, exemplified by vision transformers, have

[7]https://yann.lecun.com/exdb/mnist/
[8]https://www.image-net.org/
[9]CNN architecture, designed by Alex Krizhevsky in collaboration with Ilya Sutskever and Geoffrey Hinton at the University of Toronto in 2012

further enhanced the capabilities of recognition systems. These models utilise attention mechanisms to capture long-range dependencies and contextual information, surpassing the limitations of traditional CNNs [27].

CNNs, particularly ResNet-50, are widely utilised due to their capability to extract robust visual features. Studies have shown that ResNet-50 achieves high accuracy in identifying objects with varying attributes and appearances, a critical aspect for handling the heterogeneity of LF items such as electronics, accessories, or apparel [3], [12], [28]. Similarly, You Only Look Once (YOLO) models, including YOLOv7, are renowned for their real-time detection capabilities, ensuring low-latency processing and high precision even in challenging environments such as low light or cluttered backgrounds [29], [30].

ResNet-50, short for Residual Neural Network with 50 layers, has a DL architecture designed to address the vanishing gradient problem in very deep neural networks. It introduces shortcut connections, or residual blocks, that allow gradients to flow more effectively during backpropagation, ensuring better convergence during training. ResNet-50 has become a standard in computer vision tasks due to its balance of depth and computational efficiency, making it suitable for extracting intricate visual features from diverse datasets [25]. Its ability to generalise across object categories makes it a reliable choice for LF management applications. YOLO is an object detection algorithm known for its speed and accuracy. Unlike traditional methods that scan an image region by region, YOLO processes the entire image in a single pass, predicting bounding boxes and class probabilities simultaneously, which significantly reduces computation time while maintaining high detection precision. YOLOv7, a more recent iteration, builds on these strengths by introducing architectural improvements for better performance in real-time scenarios, including high-density environments like traffic monitoring [31], [32].

Object recognition models can struggle with computational intensity, requiring significant resources for training and deployment [33], [34]. Lightweight versions of models are being developed to mitigate these issues, particularly for mobile applications, which are essential for systems designed to be universally accessible. Mobile-compatible frameworks, using optimised CNN, provide the added advantage of enabling real-time item reporting and retrieval through user-friendly interfaces, expanding the reach of such systems [28], [35].

Furthermore, these systems still need to contend with the diverse characteristics of objects. Items with subtle features or ambiguous shapes often pose difficulties for detection algorithms. Addressing this requires extensive and diverse datasets for training and validating in order to ensure that models can generalise effectively without overfitting to specific item categories [3], [12], [29]. Hybrid approaches that integrate multiple algorithms or modalities are emerging as strategies to overcome these limitations. For instance, combining cloud-based data synchronisation with multimodal recognition has improved retrieval rates by facilitating large-scale processing and analysis [30], [36].

2.3.3 Natural Language Processing

NLP is a multidisciplinary field at the intersection of linguistics, computer science, and artificial intelligence, enabling machines to process, understand, and generate human language. NLP encompasses two core subfields: NLU and Natural Language Generation (NLG) [37]. NLU focuses on interpreting and extracting meaning from textual or spoken language, including tasks such as sentiment analysis, intent recognition, and entity extraction, allowing systems to comprehend user input and respond accordingly [37]. In contrast, NLG involves creating coherent and contextually appropriate textual or spoken output from structured data, such as generating summaries, reports, or conversational responses [38].

The origins of NLP date back to the 1950s, when Turing [39] proposed the concept of machine intelligence in his seminal work "Computing Machinery and Intelligence". One of the early milestones was the development of the Georgetown-IBM experiment in 1954, which demonstrated automatic translation between Russian and English, albeit limited to a small vocabulary and specific grammatical constructs. This marked the beginning of using computers to process and understand human language [40]. About 50 years later, in the 1990s and early 2000s, ML algorithms, mainly supervised learning, began to dominate NLP, enhancing part-of-speech tagging, named entity recognition, and sentiment analysis. This era also witnessed the rise of the first large-scale resources for NLP, including the Penn Treebank[10] and WordNet[11], which provided valuable training data and lexical knowledge [41], [42].

More recently, the new era has been characterised by a revolution in NLP fueled by DL. Neural network architectures, particularly recurrent neural networks and their derivatives, long short-term memory networks, demonstrated remarkable capabilities in sequence-to-sequence tasks such as translation and text summarisation [43]. Furthermore, the introduction of attention mechanisms and transformer-based models, such as Bidirectional Encoder Representations from Transformers (BERT) and Generative Pre-trained Transformer (GPT), has drastically improved the state of the art, enabling unprecedented performance across a wide range of NLP tasks [44], [45]. Today, NLP continues to evolve, integrating cutting-edge advancements in AI, including transfer learning and pre-trained language models, to achieve higher accuracy and efficiency in a variety of complex tasks, namely sentiment analysis, machine translation, and conversational agents [46].

The systematic review highlights the growing role of NLP in intelligent systems, particularly in enhancing human-computer interaction and automating complex processes. For instance, NLU is central to enabling systems to interpret user input, extracting key entities, sentiments, and intents. Prawira and Saputri [3] and Ghazal *et al.* [28] , have already adopted these capabilities in their LFMS to streamline the reporting and retrieval of lost items. By leveraging NLU models, their systems can process user descriptions into structured data that, once properly stored and indexed, can later be matched against found items.

Despite these advancements, several challenges remain. Scalability and computational efficiency are ongoing concerns, particularly when deploying NLP models in real-time applica-

[10] https://catalog.ldc.upenn.edu/docs/LDC95T7/cl93.html

[11] https://wordnet.princeton.edu/

tions. Additionally, ethical considerations, including bias in language models and data privacy, require attention to ensure the responsible use of NLP technologies [3].

2.3.4 Multimodal Matching

Embeddings play a pivotal role in modern artificial intelligence, particularly for applications requiring the integration of multimodal data such as images and text. These embeddings transform high-dimensional data into a lower-dimensional vector space while preserving semantic relationships. For example, image embeddings are often generated using CNN, whereas text embeddings leverage transformer-based models [25], [45]. This dimensionality reduction enables efficient and meaningful comparisons across large datasets.

Similarity search is a cornerstone technique in embedding-based systems. Prawira and Saputri [3] and Ghazal *et al.* [28] have experimented with metrics such as cosine similarity and Euclidean distance in order to quantify the proximity between embeddings, offering probabilistic measures of match likelihood between simulated LF items. A high cosine similarity score, for instance, suggests strong alignment between query and database entries. Probabilistic models can further refine these measures, incorporating confidence intervals that guide the decision-making [27].

Considering the domain of LF management, embeddings would facilitate the matching of user-provided data to stored items or records. Visual embeddings derived from processed uploaded images would be compared against a database of known items. Similarly, textual embeddings generated from user descriptions and interactions could be matched to metadata or textual entries in the database. When combined, these approaches improve the accuracy and robustness of the matching process [3], [47]. For instance, the integration of image and text embeddings through models like Contrastive Language-Image Pre-training (CLIP) enables effective multimodal matching by aligning visual and textual information in a unified vector space [47].

On the one hand, embedding-based systems face challenges related to scalability, bias, and computational demands. Scaling these systems to handle large datasets requires optimisation techniques such as lightweight models or distributed computing [33]. Moreover, biases inherent in pre-trained models can affect fairness, mainly when embeddings are derived from imbalanced datasets [3]. On the other hand, despite these challenges, empirical studies underscore the efficacy of multimodal matching in LFMSs. For instance, Prawira and Saputri [3] achieved a 97.92% matching accuracy by integrating ResNet embeddings with cosine similarity. Ghazal *et al.* [28] demonstrated an 89.2% retrieval accuracy using a multi-feature image matching approach that incorporated texture, shape, and colour features.

2.4 In-Production Lost-And-Found Management System

The management of LF items has evolved over the years, resulting in modern LFMSs that leverage innovative features. This section delves into some of the most prominent LFMSs, grouped by their functionality and strengths. All the systems that are going to be explored combine with integrated shipping and return subsystems, which expresses the importance of this feature in the context of LF management.

Comprehensive and Feature-Rich Solutions

NotLost[12] stands out as a highly versatile LFMS, offering a broad array of features that make it suitable for organisations of all sizes. Its robust automated matching and search capabilities, powered by some rudimentary artificial intelligence, simplify item identification and matching processes. The platform also emphasises data security and compliance, but despite its many strengths, NotLost lacks features for disposal and recycling, leaving room for improvement in managing unclaimed items.

Similarly, Chargerback[13] offers an extensive feature set comparable to NotLost, with added emphasis on reporting and analytics and disposal and recycling management, making it an ideal choice for organisations that require comprehensive reporting tools to analyse LF trends. Chargerback also has the best-found training and support, featuring online training and support, tech support, innovation support and a 24-hour quick response system for partners, which helps organisations onboard their staff effectively.

Specialised Solutions for Targeted Needs

For organisations seeking user-centric platforms, iLost[14] and FoundHero[15] offer intuitive, user-friendly interfaces that facilitate easy reporting and claiming of LF items. While iLost shines in its focus on simplicity and efficiency for smooth item recovery, it lacks advanced features like automated matching and analytics. On the other hand, FoundHero emphasises customer feedback collection, which enables organisations to gather valuable insights from users on their LF experiences.

Crowdfind[16] also prioritises usability, with a strong emphasis on visual tools such as photo-driven item searches. Its scalability and adaptability across multiple sectors make it a preferred choice for organisations managing large-scale LF operations.

Industry-Specific Solutions

ILeftMyStuff[17] caters specifically to the hospitality industry, offering specialised tools like automated guest communication via its communication tools. Its focus on these features, along with robust training and support, ensures that hotels and similar establishments can manage LF items without massive complaints and the need for intensive learning. However, the platform lacks support for advanced analytics and customer engagement features, limiting its broader applicability.

[12] https://notlost.com
[13] https://www.chargerback.com
[14] https://ilost.co
[15] https://foundhero.com
[16] https://www.crowdfind.com
[17] https://www.ileftmystuff.com

Community-Driven and Volunteer-Based Solutions

In contrast to enterprise-focused solutions, LostMyStuff[18] takes a community-driven approach. The platform connects individuals with volunteers to aid in recovering LF items. While it lacks advanced technological features, its focus on volunteer and community engagement makes it unique in fostering a sense of shared responsibility and collaboration among users.

Summary

The Table 2.3 summarising the features of these LFMS platforms provides a detailed comparison of their features and capabilities, highlighting the strengths and limitations of each solution.

Table 2.3: Feature Availability in Lost-And-Found Management Systems

	ILIM	AMS	UFI	CT	ISR	DSC	SMSA	DRM	RA	VCE	CFC	TS
NotLost	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	-	-	-
iLost	Yes	No	Yes	Yes	Yes	-	-	No	-	-	No	-
ILeftMyStuff	Yes	-	Yes	Yes	Yes	-	-	No	-	No	-	Yes
ReclaimHub	Yes	No	Yes	Yes	Yes	-	No	Yes	Yes	No	-	No
Crowdfind	Yes	Yes	Yes	Yes	Yes	-	Yes	-	No	No	-	-
Chargerback	Yes	Yes	Yes	Yes	Yes	-	Yes	Yes	Yes	No	No	Yes
MissingX	Yes	No	Yes	Yes	Yes	-	Yes	Yes	Yes	-	-	-
FoundHero	Yes	No	Yes	Yes	Yes	Yes	-	-	Yes	-	Yes	-
LostMyStuff	Yes	-	Yes	-	Yes	-	-	No	-	Yes	-	No

ILIM - Item Logging and Inventory Management, AMS - Automated Matching and Search, UFI - User-Friendly Interfaces, CT - Communication Tools, ISR - Integrated Shipping and Returns, DSC - Data Security and Compliance, SMSA - Scalability and Multi-Sector Adaptability, DRM - Disposal and Recycling Management, RA - Reporting and Analytics, VCE - Volunteer and Community Engagement, CFC - Customer Feedback Collection, TS - Training and Support.

2.5 Designing an Intelligent Inventory Management System for Lost-and-Found

2.5.1 Optimal Approaches

Todo: Write this section.

2.5.2 Best Practices

Todo: Write this section.

[18] `http://www.lostmystuff.net/`

CHAPTER 3

Methodology

"The things we lose have a way of coming back to us in the end,
if not always in the way we expect"
- J.K. Rowling, Harry Potter and the Order of the Phoenix (2003)

As previously mentioned, this research is separated into key stages. This section outlines the beginning of the design of the system's structure by defining its architecture, features, and workflows. To meet the acceptance criteria for this stage and take into account the volume of this research, a strategic framework was selected to guide the architectural design of the proposed solution. By leveraging the principles and steps of Architecture-Centric Development Method (ACDM), this chapter defines the solution's initial requirements, stakeholders, challenges and architecture.

3.1 Architecture-Centric Development Method

The ACDM is a software development methodology, mainly inspired by Quality Attribute Workshop, Architecture Tradeoff Analysis Method and Attribute Driven Design, that emphasises the use of software architecture as a primary driver for the development process [48]. It integrates architectural design into the overall lifecycle of software development, aiming to improve quality, predictability, and efficiency. Below are the key aspects of ACDM based on the provided paper. ACDM is structured around the concept that software architecture serves as the backbone of the system, providing a framework for ensuring consistency, scalability, and alignment with business goals. The architecture is not only a technical construct but also a means of communication among stakeholders.

3.1.1 Definition

As shown in Figure 3.1, the ACDM organises the architectural design process into clearly defined stages that evolve iteratively to ensure a robust, well-aligned system architecture.

ACDM is inherently iterative, with the flexibility to revisit earlier stages based on findings or changing requirements.

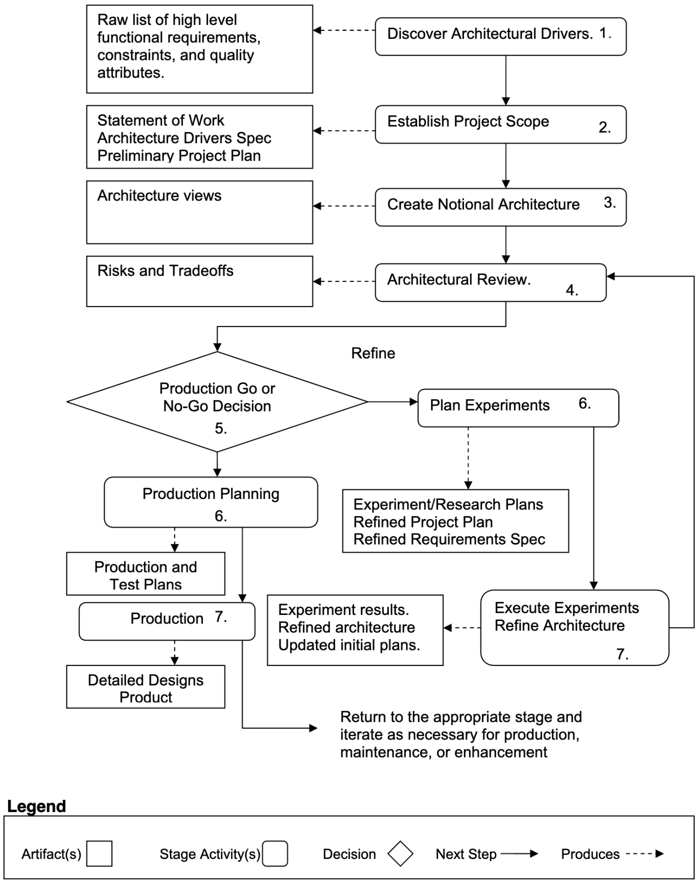

Figure 3.1: ACDM workflow, illustrating the iterative stages, the flow of artifacts, decisions, and refinements through the development process. Adapted from Lattanze [48] .

Architectural Drivers

According to Lattanze [48] , the process begins with discovering the architectural drivers, where critical factors such as functional requirements, quality attributes (e.g., performance, scalability, security), and constraints are identified. These drivers form the foundation for all subsequent design decisions.

Project Scope

Following this, the project scope is established to define the system's boundaries, objectives, deliverables, and constraints, ensuring all stakeholders have a shared understanding of the project's limits and expectations.

Notional Architecture

Once the drivers and scope are defined, a notional architecture is created as a high-level conceptual design. This step involves decomposing the system into components, defining their responsibilities, interactions, and dependencies, and adopting appropriate architectural styles and patterns. The notional architecture serves as a blueprint for early-stage validation.

Architectural Review

The design is then subjected to an architectural review, where it is assessed against the architectural drivers and project scope. Scenario-based evaluations, risk assessments, and stakeholder feedback are key activities during this stage. The outcome is a decision to either proceed to production or refine the architecture further.

Refinement Phase

If the architecture is deemed insufficient during the review, the process enters a refinement phase. This phase begins with the **experiment planning**, where targeted experiments are designed to address specific weaknesses or uncertainties, such as performance bottlenecks or scalability challenges. These experiments are executed in the **experiment execution** and subsequent **architecture refinement** stage, with findings informing updates to the architecture. Once refined, the updated architecture undergoes another review to ensure it meets the required standards before moving forward.

Production Phase

If the architecture passes the review, the process transitions to the production phase, beginning with the **production planning**, which involves preparing the system for deployment by developing detailed plans, establishing monitoring mechanisms, and ensuring operational readiness. Finally, the system is deployed during the **production** stage, when it becomes operational and accessible to end-users. Post-deployment, the architecture is continuously monitored for performance and feedback, allowing iterative improvements as needed.

3.1.2 Quality Attributes

The quality attributes serve as a foundation for developing the platform. The selection of the following attributes was guided by their critical role in ensuring the solution's success and addressing the key challenges identified in the problem domain.

The following quality attributes were selected based on their priority to the solution's success and the challenges identified in the problem domain.

Scalability

The platform must accommodate a growing user base and increased item-tracking demands across diverse locations. A microservices architecture is proposed to enable independent scaling of critical system components, such as user management and item management. This scalability aligns with the goal of creating a community-oriented system capable of handling high-traffic scenarios and fluctuations in demand without compromising performance.

Reliability

Consistent performance is critical, even in adverse conditions like network failures. Ensuring reliability contributes to fostering user trust, a cornerstone of a lost property management system, aiming to build credibility among stakeholders. Fault-tolerant mechanisms, such as distributed databases and redundant servers, will be integrated to ensure high availability (targeting 99% uptime) and minimise the "mean time to repair"[1]. Automated monitoring and self-healing protocols will detect and address faults proactively.

Security

Handling sensitive data, such as user information and potentially high-value lost items, requires a security-first approach. Security measures further reinforce the platform's reliability and address concerns like identity theft and elevated access, two key pain points identified in this research. End-to-end encryption for secure authentication and granular authorisation mechanisms will protect data privacy. Due to the sensitivity of the data the system is going to handle, it is obliged to adhere to General Data Protection Regulation (GDPR)[2] and other relevant regulations to ensure the lawful handling of personal information.

Usability

The system targets a broad spectrum of users, including non-technical individuals, necessitating an intuitive and accessible interface. Implementing User Interface (UI) and User Experience (UX) best practices and ongoing feedback loops will ensure an iterative improvement of the platform's interface. Multilingual support and visual guidance will also cater to diverse user demographics.

Observability

Incorporating observability tools to collect logs, metrics, and traces will allow real-time and long-term monitoring of the system's performance and user interactions. Observability also allows quick detection and resolution of operational issues, providing insights for continuous improvement.

3.1.3 System Requirements

The system's design and implementation are guided by its requirements, which can also be used to measure the research progress and value. When correctly specified, they help the developer understand the expected result, and the stakeholders evaluate the system's performance. These requirements are divided into two categories: functional and non-functional. Table 3.1 lists the functional requirements that define the core features of the system, focusing on enabling users to interact with and manage data effectively.

On the other hand, Table 3.2 presents the non-functional requirements, which ensure that the system remains with the expected quality levels.

The remaining requirements are fully detailed in the appendix.

[1] `https://www.atlassian.com/incident-management/kpis/common-metrics`
[2] `https://gdpr-info.eu/`

ID	Functional Requirement Description
FR1	Support three user roles: ordinary users, local managers, and administrators.
FR2	Enable secure account management for all user types.
FR3	Implement authentication and authorization mechanisms, including multi-factor authentication.
FR4	Allow users to browse and search lost items based on categories and filters (e.g., location, type).
FR5	Provide personalized suggestions for matching items using AI.
FR6	Facilitate item status updates and notifications to users about item matches or updates.
FR7	Enable users to schedule appointments for item retrieval.
FR8	Allow administrators to audit system logs and manage user roles effectively.
FR9	Integrate community-driven features for collaborative lost item recovery.

Table 3.1: Functional requirements defining the core system features.

ID	Non-Functional Requirement Description
NFR1	Ensure a response time of less than 2 seconds for critical operations under peak load.
NFR2	Support scalability to accommodate up to 10,000 concurrent users.
NFR3	Comply with data privacy regulations such as GDPR.
NFR4	Maintain 99% uptime through fault tolerance and disaster recovery mechanisms.
NFR5	Adhere to UX and UI best practices.
NFR6	Implement modular and maintainable architecture for easier updates and debugging.
NFR7	Incorporate monitoring tools for real-time performance tracking and troubleshooting.
NFR8	Ensure compatibility across devices.

Table 3.2: Non-functional requirements defining the system's quality attributes.

3.1.4 Constraints

The development of the system is governed by two primary constraints that shape its scope, deliverables, and quality:

C1: Timeframe Limitation

The development is restricted to a 10-month timeframe in which it is embedded.

C2: Verifiable Quality

Both software and design quality must be verifiable, meaning the stakeholders must test the system and review its code.

3.1.5 Notional Architecture

The proposed architecture, visible in Figure 3.2, is designed as a microservices-based system, i.e., it divides the application into distinct, independent services, each responsible for a specific functionality. It is possible to group the architecture's components into three main layers: the frontend, backend, and support infrastructure, as follows:

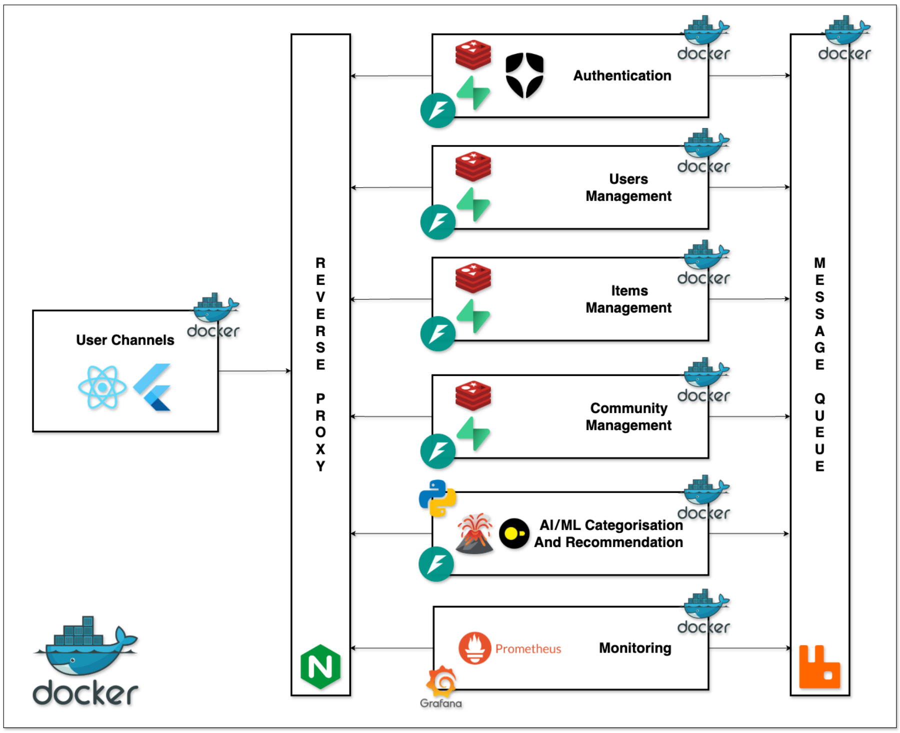

Figure 3.2: High Level View of the First Iteration of the Notional Architecture.

Frontend

The frontend provides users with a seamless and intuitive interface for both web and mobile platforms, enabling easy access to all system features and smooth interaction with the backend services.

Backend

The backend is the core of the system and is structured as a collection of microservices that include:

- Authentication Service: Through the use of role-based access control, it handles user authentication and authorisation, ensuring secure access to the system;
- Users Management Service: Manages user profiles, including registration and updates;
- Items Management Service: The most likely core service of the system focuses on fetching, storing and updating lost items. It integrates with other services to provide seamless item tracking and retrieval functionalities;
- Community Management Service: Handles the direct communication between ordinary users and the chat spaces available for each community;
- AI/ML Categorization and Recommendation Service: Automatically identifies and categorises items based on images and descriptions. Processes user inputs and interactions to actively match and recommend items to ordinary users who search for an item.

Support Infrastructure

The infrastructure provides the foundation for deploying and managing the system. It includes the following key components:

- Reverse Proxy: Routes incoming requests to the appropriate services. It also provides load balancing and enhances the system's overall security by handling HTTPS termination;
- Message Queue: Facilitates asynchronous communication between microservices, ensuring that each service operates independently, even during high data throughput;
- Monitoring: Collects performance metrics and provides a dashboard for real-time visualisation.

Tech Stack

For the frontend, React[3] is used to build dynamic and interactive web applications, while Flutter enables cross-platform mobile application development, ensuring consistent user experiences across devices. The backend is powered by FastAPI[4], a Python[5]-based framework that excels at building high-performance Application Programming Interfaces (APIs), supporting asynchronous operations, and type validation. Authentication is secured using OAuth 2.0[6], a widely adopted protocol for granting and managing secure access.

The system relies on Supabase[7], an open-source backend-as-a-service, for handling database operations, real-time data sync, and authentication, complemented by Redis[8] for caching and session management, ensuring fast data access and reducing backend load. For AI-driven functionalities, Large Language and Vision Assistant (LLaVA)[9] combines language and vision processing. Data analytics are supported by DuckDB[10], an in-process analytical database that efficiently processes the complex embeddings generated by LLaVA.

To ensure robust monitoring, Prometheus[11] collects metrics across the system, and Grafana[12] provides intuitive dashboards for real-time visualisation and performance tracking. The entire infrastructure is containerised using Docker[13], ensuring consistency across environments and simplifying deployment. Nginx[14] acts as a reverse proxy and load balancer, enhancing request routing, security, and scalability. Finally, RabbitMQ[15] serves as the message broker, enabling asynchronous and reliable communication between microservices, which is critical for the system's modular and distributed architecture.

[3] `https://react.dev/`
[4] `https://fastapi.tiangolo.com/`
[5] `https://www.python.org/`
[6] `https://oauth.net/2/`
[7] `https://supabase.com/`
[8] `https://redis.io/`
[9] `https://llava-vl.github.io/`
[10] `https://duckdb.org/`
[11] `https://prometheus.io/`
[12] `https://grafana.com/`
[13] `https://www.docker.com/`
[14] `https://nginx.org/en/`
[15] `https://www.rabbitmq.com/`

3.2 Future Work and Work Plan

The next phase involves the implementation of the proposed architecture, starting by creating a MVP to test the initial functionalities. The MVP will focus on the item management service, user registration and authentication, and the community management service. The MVP will be iteratively refined based on user feedback and performance metrics, ensuring that the system meets the acceptance criteria defined in this research. This MVP will integrate most of the IMS features and is expected to be a full LFMS, capable of handling lost items and user interactions. The AI/ML categorisation and recommendation service will be developed in parallel to the MVP testing and will be integrated into the system once it reaches a stable state, resulting from the feedback and improvements made. Once the service responsible for the system's intelligence is integrated, the system will, once again, be tested and refined to ensure that the functionalities are working as expected and that the system meets the acceptance criteria and fulfils the architectural drivers and the dissertation's objectives.

The dissertation document will be continuously updated throughout the system's development to reflect the progress made. It will also include the system's testing results and the feedback received from users and stakeholders. The final version of the document will include a detailed analysis of the system's performance and usability, as well as a discussion of the lessons learned and the potential for future research.

Figure 3.3 illustrates the work plan for the next phase, outlining the key activities and milestones to be achieved.

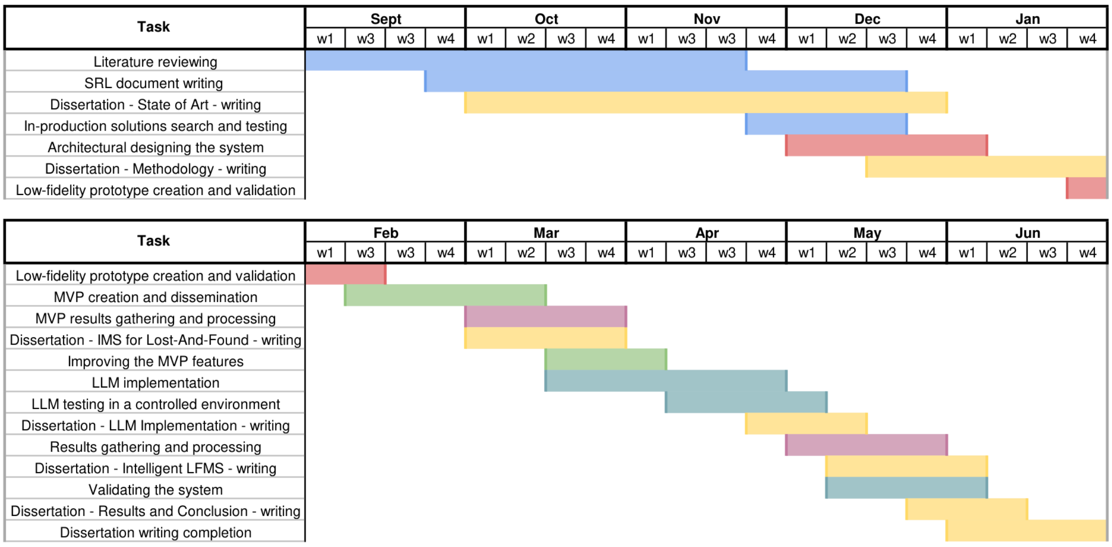

Figure 3.3: Expected dissertation's work plan expressed in a Gantt diagram.

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