BSc Artificial Intelligence and Computer Science
2455269

A systematic approach to improving outfit suggestions
by
Hasan Shariff.

School of Computer Science
College of Engineering and Physical Sciences

Final Year Project Dissertation

Supervisor: **Rami Bahsoon**
Consultant: **Michael Oakes**

University of Birmingham 2024-25

I declare that this dissertation, which has been completed as part of my Undergraduate studies at the University of Birmingham, has been completed independently. All relevant resources and information sources have been listed.

University of Birmingham, 17.05.2025 Hasan Shariff

Word Count:

Contents

1 Acknowledgments

I would like to thank...

2 Abstract

3 Key Words

This is a list of key words and terminology used throughout this paper.

1. UI - User Interface
2. UX - User Experience

4 Introduction

4.1 Overview

The primary objective of this project is to generate outfits for users based on what they have in their wardrobe. The user will be able to take photos of items in their wardrobe and upload them to the system's database. Once the user is happy with the images that they have uploaded then they can generate outfit based on what they have.

4.2 Introduction

The fashion industry is one of the fastest growing sectors in the world with it currently representing 1.65% of the global gross domestic product. This industry is expected to see a compound annual growth rate of 2.81% between 2025 and 2028 [1]. Driven by the rise of e-commerce couple with social media platforms such as Instagram and TikTok these platforms have revolutionised access to the latest clothing trends and items. While on the surface, this scale of accessibility appears to be a substantial benefit. In reality this presents a considerable challenge and concerning patterns of over consumption and wardrobe underutilisation. This claim was supported by a study conducted in 2022 by the UK charity WRAP. WRAP revealed that at least one quarter, 26-31% of the average person's wardrobe remains unworn for at least 1 year [2]. This claim was further supported by the UK based retailer Marks and Spencers who further confirmed this issue. They found that in the average wardrobe which consists of 152 items only 44% of those items are worn regularly [3]. This widespread underutilisation demonstrated by both studies suggests that is a significant problem representing significant environmental challenges through increased carbon footprints, economic waste and textile accumulation.

This project will aim to address this challenge by developing an intelligent outfit recommendation system with the main purpose to help the user rediscover, maximise and optimise their existing wardrobe. The proposed system will leverage several different domains of artificial intelligence and machine learning to aid in the generation process of outfits based on the users wardrobe while keeping the main aim of maximising the user's wardrobe. By aiming to consistently achieve this aim project seeks to reduce unnecessary purchases and their associated environmental impact while working towards the goal of maximising the potential of the user's wardrobe.

This proposed system will leverage several artificial intelligence capabilities including object detection for accurate classification of the item, background removal for clean image processing, feature extraction to identify and utilise the key features of the item of clothing and finally adaptive learning to refine recommendations based on user preferences and feedback. These technologies work hand in hand with each other to create a comprehensive proposed solution that intelligently analyses the user's wardrobe to suggest optimal outfit combinations.

This report will detail the information about the motivations behind the project and how the project was managed over time. In addition to this the report will also explore the fundamental system, requirements necessary and the design principles and decisions taken. This report will also explore the implementation of different artificial intelligence aspects as well as the user centric design. Furthermore it will delve into how all of the different aspects tie together, finally culminating in the demonstration of the success of achieving the main principle and aim of maximising and fully utilising the user's wardrobe.

5 Literature Review and Research

5.1 Object Detection and Image Classification

The object detection algorithm presented by Lao and Jagadeesh in their paper presents a comprehensive CNN-based framework for fashion classification and object detection across different domains of challenges. This implementation demonstrates the effectiveness of CNNs in fashion classification with a validation accuracy of 93.4% [4]. However, the methodology exhibits some limitations, such as struggling to accurately define two classes which are difficult to visually distinguish. This implementation also predominantly uses controlled datasets, which are not comparable to real-world scenarios where insufficient lighting, poor image quality, or complex backgrounds predominate. This work does, however, provide valuable methodological insights for implementing object detection within fashion applications.

Feng et al.(2018) presented an object detection implementation using the YOLOv2-opt system which is an enhancement on the YOLOv2 architecture. The demonstrated system achieves high levels of accuracy and precision while also maintaining its speed. The model was trained on a dataset containing five categories (trousers, skirts, coats, T-shirts and bags) which varied in detection performance. The model performs better on items with more well-defined borders which results in higher precision 93.5% [5]. Despite these promising results, this model does however present some limitations such as misidentifying objects with more complex backgrounds. This includes the model thinking a dark region within an image was a bag. The authors suggest that "the model needs to be enhanced in processing complex images". Another limitation in this paper is the relatively small dataset as a significant constraint. This research demonstrates the potential of deep learning approaches for fashion detection.

5.2 Optimised Based Matching System

Cross and Hancock present a methodologically sophisticated framework through stochastic optimisation which offers valuable insights for outfit recommendation systems. Optimisation-based matching can be applied to outfit recommendation as it allows for discovering globally optimal combinations in highly complex style compatibility spaces where stable matching fails to capture nuanced fashion relationships. The authors, Cross and Hancock, compare multiple stochastic optimisation strategies such as genetic algorithms. Their genetic algorithms achieve “rapid and uniform convergence to a global optimum” [6] whereas deterministic methods become trapped in local optima. These findings by Cross and Hancock suggest that optimisation-based matching has profound implications for outfit recommendation systems where it avoids inconsistent suggestions. Furthermore, the genetic approach in this paper maintains the use of weighted matching configurations which draws parallels with multiple style combinations with varying degrees of compatibility. This paper was initially intended for aerial imagery matching however the optimisation framework can be adapted to model relationships between different items of clothes where, similar to a decision tree nodes represent items and edges denote style compatibility. This ultimately results in more robust and globally optimal outfit suggestions.

Mills-Tettey et al. present the dynamic Hungarian Algorithm which is an advancement on the standard implementation of the Hungarian algorithm formulated by Kuhn-Munkres. This dynamic approach efficiently aims to solve and repair existing solutions achieving $O(kn^2)$ complexity where K is the number of modifications. The authors prove that their solution achieves optimality faster through empirical testing that their method runs “orders of magnitude more efficiently” [7]. This implementation also presents promise to optimising outfit suggestions where outfit compatibility scores may fluctuate depending on situational changes such as an alteration to the wardrobe. This can then be applied to outfit suggestions where each node in the Hungarian algorithm represents an individual item and the edges represent compatibility. This optimisation framework set out by Mills-Tettey allows for efficient and responsive outfit recommendation systems.

5.3 Adaptive Learning for Outfit Recommendations

Majeed et al’s reinforcement learning implementation for personalised clothing recommendations establishes feasibility for personalised outfit recommendations via real time user interaction mechanisms. The research aims to refine the recommendation process over time but also increase user satisfaction with more personalised outfits. The authors want to ensure that the clothes that are recommended cater to the individual and their style preferences based on the responses from the user [8]. Despite achieving notable accuracy this implementation does exhibit some limitations, such as using a specific dataset which encompasses only a limited set of pants and shirts. The experimental design also predominantly emphasises parameter optimisation rather than incorporating multiple user attributes such as preference hierarchies or gender specific considerations. Another limitation resides in the absence of user acceptance testing leaving the system unevaluated in real world applications. Despite these challenges this paper does lay the foundations for using reinforcement learning and adaptive learning in recommendation domains.

The machine learning based outfit recommendation system developed by Kokane et al leverages a comprehensive dataset of clothing items while also incorporating body-shape analysis [9]. This system does present promise in increasing personalised fashion recommendations using several domains of artificial intelligence. While the system does demonstrate promise in personalising outfit recommendations there some limitations that should be addressed. Firstly the dataset struggles in diversity and representativeness which may skew the system. In addition the implementation could be susceptible to ethical issues as body shape analysis requires the use of biometric data and the report does not mention how this information is stored and protected. This research does suggest that a machine learning approach represents a significant advancement for personalised fashion recommendation systems.

5.4 Existing Works

While there is an adequate amount of research on intelligent outfit recommendation systems, there are relatively few digital applications in actuality. These existing applications primarily server as digital wardrobe organisers or tools to enhance e-commerce, however fail to utilise the advanced methods discussed in the literature review. Examples of this include Uniqlo's implementation which lets users combine items from new collections to create outfits manually. On the other hand, FItted-AI enables users to upload images of their clothing and then randomises outfit suggestions. These implementations demonstrate there is significant scope for technological approaches to outfit recommendations.

5.4.1 Outfit Recommendation for E-Commerce

Uniqlo is one of the world's largest retailers and in order to enhance the e-commerce experience they have implemented an outfit generation system. This system allows users to create outfits manually by selecting items from Uniqlo's website which are in the latest collections. Then based on what the user selects the system will then create an outfit for the user. This is a very simple implementation however, it gives the user full control over how the outfit is generated. This implementation is limited by not fully leveraging artificial intelligence in addition to not having an affective matching system. The dataset used is also very limited as it only focuses on clothes which Uniqlo's sell rather than using items from the user's wardrobe. This implementation serves as a baseline for other methods as there is minimal algorithmic assistance.

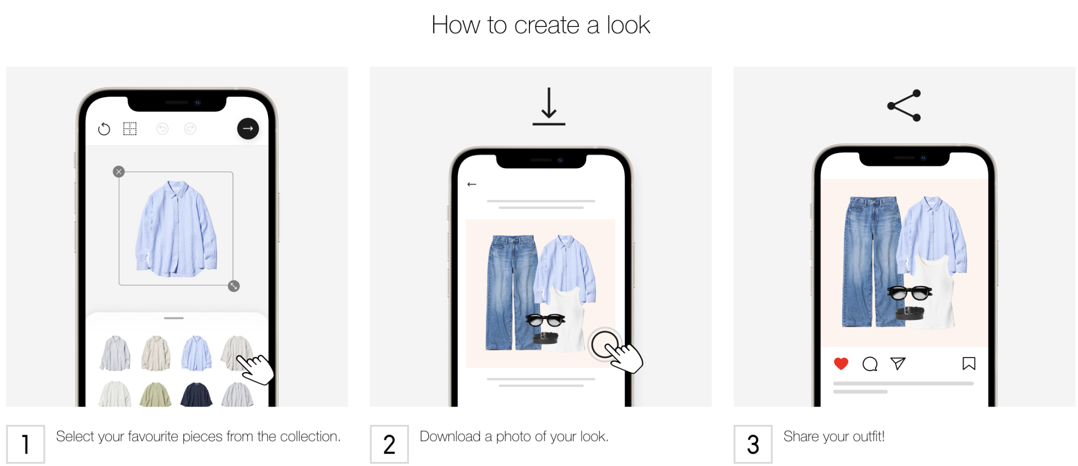

Figure 1: Uniqlo Workflow [10]

5.4.2 Outfit Recommendation for mobile apps

Fitted-AI represents a mobile application implementation for outfit recommendation systems which apply artificial intelligence techniques discussed in the literature review. The app does employ an object detection model to classify images uploaded by the user and it does also automatically label the images. Users are also able to generate outfits using the "create a fit" button which randomly selects four items of clothing across different categories (headwear, top, trousers and shoes). However the implementation does exhibit significant limitations. Firstly, the system lacks any form of robust validation mechanisms, this leads to the system failing to verify if the uploaded images actually contain items of clothing leading to non-clothing items being used In outfit generation. Furthermore Fitted-AI heavily relies on simple randomisation rather than style compatibility algorithms, this limits the user from expressing individuality and style preferences. In addition to this the practical utility of the app is limited as the application limits the wardrobe size before implementing a pay wall. Despite these limitations Fitted-AI does demonstrate the viability of mobile-based outfit recommendation systems.

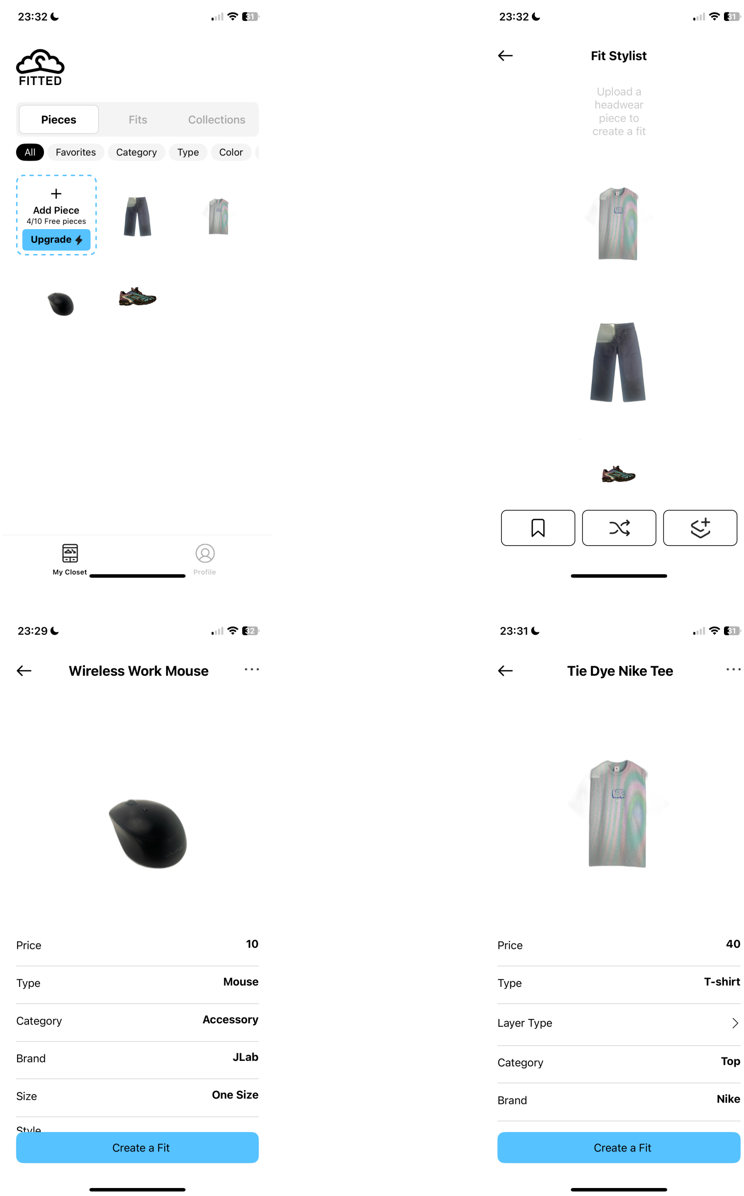

Figure 2: Fitted-AI [11]

6 Initial Research

7 Project Management

Due to the nature of this project, a significant amount of research had to be conducted to fully comprehend the working components of this proposed outfit suggestion system. Subsequently, initial user research was then conducted to fully understand what potential users wanted to gain from the app and to gain more insight into what functional and non-functional requirements were necessary. These requirements laid the foundations for the implementation stage of production. After this, the user interface was then designed with a user-centric design process. During the development phase, it became very clear that some features had to be developed concurrently, whereas other features could be developed sequentially. However, most of the design and implementation process happened concurrently. After development was complete, tests were carried out to measure the efficacy of the implemented system. Such tests included unit tests and user acceptance testing.

This Gantt chart in Figure 3, shows the timeline taken for the completion of the project as well as all of the milestones which were achieved along the way.

In addition to using the Gantt chart to illustrate the project schedule, the project was also managed through the use of Agile principles most notably Kanban cards. These cards were created to track and maintain different tasks which were vital to the production process of this project. All resources and notes taken during the development of the project were recorded using Pages. In order to maintain the security and integrity of the project GitHub was utilised. This allowed for effective commits of new updates to the project as well as insightful comments to label each commit. GitHub was also used for version control enabling the ability to reverse anything. Git however did struggle as it was unable to receive the object detection model due to its size. Finally, meetings with my supervisor were conducted each week to get valuable feedback and insights into the design process from my supervisor and colleagues. These meetings were also used to report progress each week.

7.1 Gantt Chart

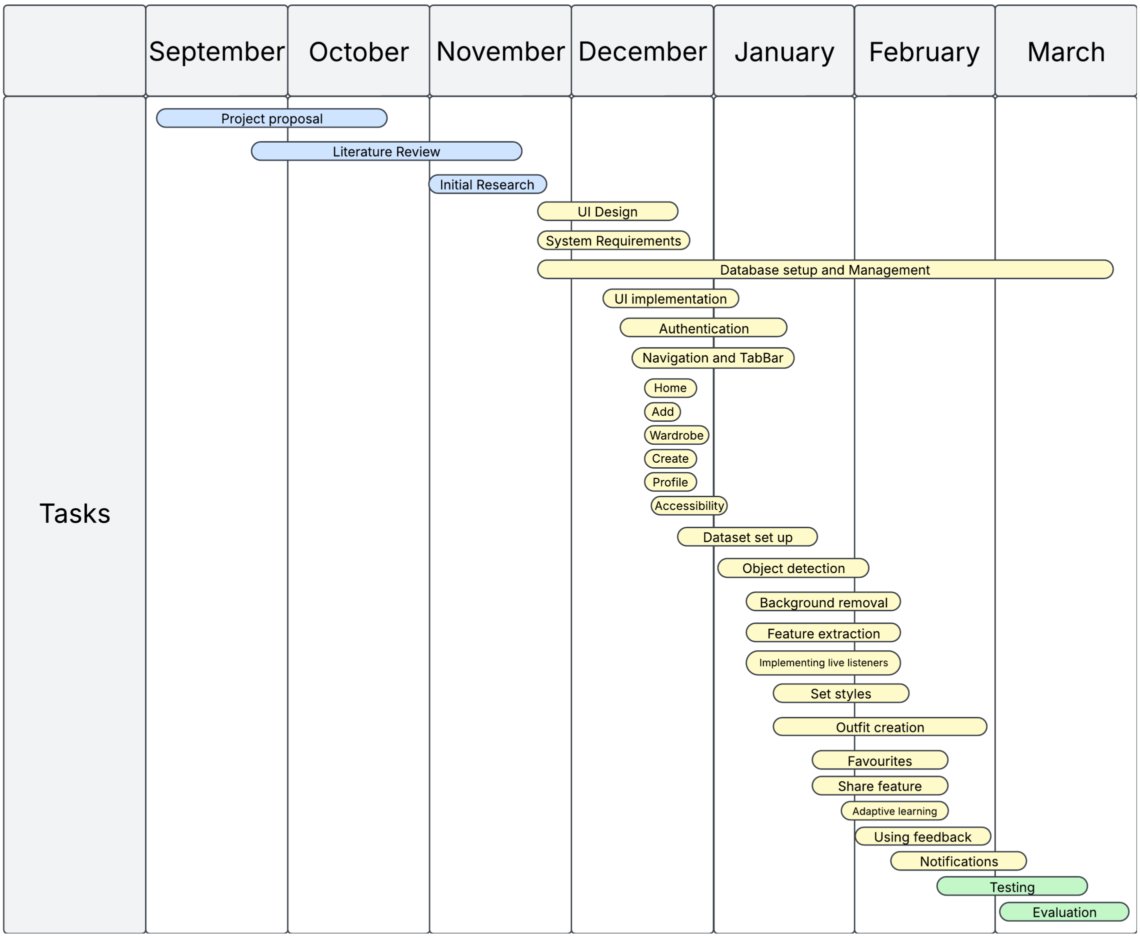

Figure 3: Gantt Chart

8 System Requirements

8.1 Aim

The aim of this section is to layout the fundamental system requirements that the app must adhere to, in order to ensure a strong implementation of the proposed solution. The requirements were developed to guarantee the app is designed in a user-centric manner. The following functional and non-functional requirements were developed when conducting the research phases of this project.

8.2 Requirements

The outlined functional and non-functional requirements were categorised using the MoSCoW framework situated in requirement engineering. This framework which is industry standard denotes the priority of the given requirements using a predetermined criteria “must have”, “should have”, “could have” and “will not have” [12]. The different requirements will be assigned a status based on their requirement for the project.

8.2.1 MoSCoW Categories

The MoSCoW prioritization framework consists of four distinct categories which are strictly followed to classify a requirement.

- **Must Have (Mo):** These are critical requirements for the project that must be included.
- **Should Have (S):** Important requirements with a high priority which should be included.
- **Could Have (Co):** Requirements that could be added as an extra consideration to further improve the project, however not crucial to the outcome.
- **Won’t Have This Time (W):** Requirements which are mainly considered for future works and will not be implemented in the current version.

8.3 Functional Requirements

The functional requirements listed in the table detail the methods and processes which enable users to fully interact with all features within the app. The proposed app requires user authentication functionality enabling users to sign up or log in while sharing necessary personal details.

For the digital wardrobe to realise its full potential users must be able to capture images of their desired clothing items within the app after granting camera permissions. These images will then be uploaded to the database once they have undergone extensive object detection processes other to accurately classify each garment. Each image will also undergo background removal and a degree of feature extraction. User's are able to add information to these images post processing by labelling the images before saving to the database. All of the user data which is collected throughout must be stored in a database with appropriate access restrictions.

Once a sufficient number of clothes have been added to the user's digital wardrobe the user is then able to create outfits. This step enables style selection and outfit creation. The outfits are generated using optimisation methods and matching methodologies to best match the outfit according to a selected style. One critical requirement of the system is the user must be able to interact with the suggested outfits. Should the user reject specific items then the system must adapt its recommendations accordingly.

8.3.1 Functional Requirements Table

8.4 Non-functional Requirements

8.4.1 Non-functional Requirements Table

9 Design

9.1 System Design

9.1.1 Design Challenges Overcome

9.1.2 Front-end design UI/UX

9.1.3 Back-end design

10 Implementation

11 Evaluation

12 Conclusions

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