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Article

Personalized clothing recommendation framework based on the fusion of sports biomechanics and computer vision

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Abstract: This research aims to create a novel framework that merges sports biomechanics and computer vision for automating the clothing suggesting process, with advancements in extracting biomechanical features, undertaking visual analysis, performing multimodal data fusion, and personalization modeling. The framework employs powerful computer vision techniques and deep neural networks alongside biomechanical sensors like the goniometer, pressure scanner, and other sensors capturing locomotor dynamics. In this study, for the first time, a profound fusion between multidimensional biomechanical variables and captured appealing semantic and visual components is made, with quantifiable relations between the functionality and aesthetic performance of the clothing design established. Judith, the core autonomous system, achieves high-accuracy personalized recommendations through analysis of joint movements, recognition of motion habits, and modeling of pressure distribution. In the framework, an entirely new paradigm for the clothing market is constructed by combining real and virtual models. The system solves the cold-start issue by utilizing cyclic domain transfer learning together with biomechanical features-driven analysis. The obtained results are impressive, with the system achieving a recall of 0.845, precision of 0.892, and NDCG of 0.901, as well as biomechanical-special metrics of body-fit score equal to 0.885, motion comfort 0.873, and pressure distribution uniformity 0.891. As different user groups were analyzed, the results were unchanged. This shows the framework's practical usability and sustainability. Besides, it opened up a new avenue for intelligent recommendation systems that integrate biomechanical analysis.

Keywords: biomechanical-visual feature fusion; personalized clothing recommendation; motion analysis; deep learning; multimodal data integration

1. Introduction

1.1. Background and significance

In recent times, with fast-paced advances in computer vision and deep learning, the face of the fashion world has completely changed, especially in personalizing garment recommendations [1]. The rapid integration of fashion retail with technological innovations offers immense opportunities in enhancing user experience and improving recommendation accuracy. This is because rapid development has left modern recommendation techniques, reliant on simple methods, not able to deal with the complex visual and semantic features of fashion items [2]. The challenge is how to embed a computer vision system effectively into personalization algorithms to build more sophisticated and accurate recommendation systems.

In addition, the inclusion of biomechanical evaluation and research into pin technology is deemed to be the most important development that has happened in the past few years. There is ample evidence that physiology-based approaches enhance clothing design and customization in sports and rehabilitation medicine [3]. With the development of methods for studying and simulating human actions, joint movements, and pressure patterns, the effects of clothing on a person involved in various activities began to be studied [4]. With this integration, a fundamental weakness of traditional recommendation engines is addressed, namely the focus on appearance and taste alone, with little or no attention being paid to the biomechanical characteristics of garment comfort and performance [5].

This research is very relevant with regard to its goals: It summarizes various methods of visual feature extraction that allow for better understanding and grouping of fashion products in relation to their intrinsic characteristics [6]. Its implication is huge in the fashion retail sector, where the basis of choice usually rests in the visual attributes. Also, deep learning-based frameworks have created huge potential to identify fashion attributes, opening new dimensions toward building recommendation systems that can be far more accurate and context-sensitive [7].

The fashion recommendation system has given way to a more personalized dimension, which is because of the increasing demand on behalf of the customers for a more 'tailor-made experience' [8]. Advanced systems improve their insight and foresight of user preference by fusing visual and textual information; this, in turn, improves recommendation accuracy and relevance significantly [9]. The significance of this research domain is underscored by its focus on the primary challenge of reconciling the capacities of computer vision with the modeling of user preferences [10].

On the other hand, in more recent developments in attention mechanisms for fashion learning compatibility, the system can now delve deeper into understanding the relations between different fashion items [11]. The level of this progress has significantly impacted not just the solitary retail investor but also the consumer at large, as resulting shopping experiences can be highly intuitive and therefore time-effective. The cross-domain knowledge that has been incorporated with transfer learning has also empowered these systems to handle most of the contexts of fashion with increasing abilities [12].

The research will go beyond the mere commercial significance but holds a fundamental place in the wider area of artificial intelligence, concerning interpretable and explainable recommendation systems. Particularly, this is relevant where the machines can understand and analyze data on fashion. Such an understanding of those elements is bound to be important for development and the continued improvement of working on reliable and trustworthy recommendation systems.

1.2. Current advances in global research

Both domestically and worldwide, there have been strong efforts put towards the improvement of personalized clothing recommendation systems. Multiple studies have shown how vital the application of fashion deep learning techniques has been for several years. Visual-semantic embedding approaches that have been developed globally have remarkably improved the matching of users' preferences to clothes [2], and many other researchers have stated the same. There has been an increase in the accuracy of feature extraction for fashion design elements [6], and addressing the cold-start problem has made the system more robust [7].

Global research institutes have directed their attention to creating deep learning models of fashion-diverse attributes for the recognition of fashion attributes [8]. There are wide possibilities for multi-aimed recommendation systems using both graphic and verbal data simultaneously [9]. They will allow for much more effective modeling of user taste by capturing style patterns [10] and substands of individual style.

Progress in the biomechanics of clothing assessment has been made alongside other studies focusing on garment-body interaction. Numerous sports science organizations have done remarkable work regarding the effect of clothing on sports performance, especially concerning pressure distributions, joint movement range, and muscle activation [13]. The combination of motion capture technology and clothing analysis has provided new avenues for investigating the interaction between apparel and human biomechanics [4]. These innovations have particularly affected the development of sports and medical garments, in which the apparel user’s comfort and the clothing’s functional effectiveness pose serious biomechanical considerations [14].

More recently, novel fashion attention mechanisms have been designed to assist with the understanding of fashion simultaneity [12], while inter-domain one-shot challenges in fashion recommendation systems have been solved through transfer learning [15]. At the national level, significant work is being done in modeling user preference concepts [16], while fashion attributes assessment is being revolutionized by deep feature learning [17]. The combination of hybrid recommendation approaches is proving to be more useful in practice than many had anticipated [18], which in turn suggests further progress within the direction of refinement and specification of automated recommendation systems.

1.3. Research content and innovation

This research proposes an intelligent outfit recommendation system based on large-scale deep learning methodologies through computer vision.

The main research content is as follows:

1) Visual feature extraction and analysis: Development of advanced techniques to extract and analyze visual features and attributes from clothing products.
2) Personalized recommendation algorithms: Formulation of sophisticated algorithms for generating highly personalized clothing recommendations.
3) System implementation and optimization: Design and optimization of a comprehensive system that effectively integrates all components.

The key innovations are as follows:

1) Novel feature fusion strategy: This research proposes a new feature fusion strategy that combines visual, biomechanical, and semantic attributes of garments into a single model. This integration significantly improves both clothing recognition and attribute identification performance while establishing quantifiable relationships between functionality and aesthetic performance of clothing design.
2) Biomechanical analysis integration: The system employs advanced biomechanical analysis including joint kinematics, pressure distribution, and

motion analysis to evaluate clothing functionality and comfort. This enhances understanding of body-garment relationships, particularly for sports and rehabilitation applications. The algorithm self-adjusts to accommodate user requirements by processing both explicit preferences and implicit biomechanical data.

3) Hybrid deep learning approach for cold-start problem: We developed a hybrid deep learning approach that merges collaborative filtering and content-based filtering with visual similarity metrics to address the cold-start problem. The system uses cyclic domain transfer learning with biomechanical features-driven analysis to provide meaningful recommendations despite limited user interaction history.
4) Style compatibility estimation: Our state-of-the-art work in style compatibility estimation uses attention mechanisms to comprehend complex relationships between multiple clothing items. This approach captures subtle style elements and compatibility factors across diverse categories and occasions that traditional systems might overlook.
5) Robust system implementation: The framework delivers a solid implementation platform that optimizes computational resources while maintaining high recommendation accuracy. It incorporates real-time data visualization capabilities and dynamically adapts to evolving user preferences, providing a scalable foundation suitable for large-scale commercial applications.

1.4. Essay organization

The whole dissertation contains six relevant chapters that orderly discuss the objectives. Chapter 1 describes the background, motivation, topic, and structure of the dissertation. Chapter 2 establishes the theoretical framework through a review of a number of associated theories and technologies relating to computer vision and personalized recommendation systems. It mainly includes system architecture and module design of the vision-based garment attribute analytics system in Chapter 3. Chapter 4 introduces the investigation and implementation of personalized recommendation algorithms for clothes, including user preference modeling and feature fusion methods. The realization of the system is implemented and its performance evaluation by experimental results and comparative analyses is presented in Chapter 5. Chapter 6 summarizes this thesis by describing a summary of the results and directions for future research.

2. Relevant research

2.1. Basic theory of computer vision

The theoretical foundation of computer vision forms the pivotal basis for clothing recommendation systems, amalgamating various key components imperative for image understanding and feature extraction [1]. Essentially, computer vision empowers machines to interpret and evaluate visual information obtained from clothing images through sophisticated algorithms and mathematical structures. In essence, computer vision in fashion analysis leans greatly on methodologies for feature extraction that transform the raw image data into meaningful representations [6]. These vary from basic analyses of pixels to the most sophisticated semantic interpretation of them, hence enabling profound insight into the characteristics of attire.

In the fashion analysis domain, state-of-the-art computer vision methods have lately been substantially improved with the help of deep learning frameworks [7]. In these systems, visual information is assessed through a successive hierarchy of abstraction, which, step by step, identifies more and more complex features of the original images. The ensuing section describes the process of visual feature extraction, as presented in **Figure 1**, explaining the inherent hierarchical framework of the computer vision analysis exploited in fashion recommendation systems.

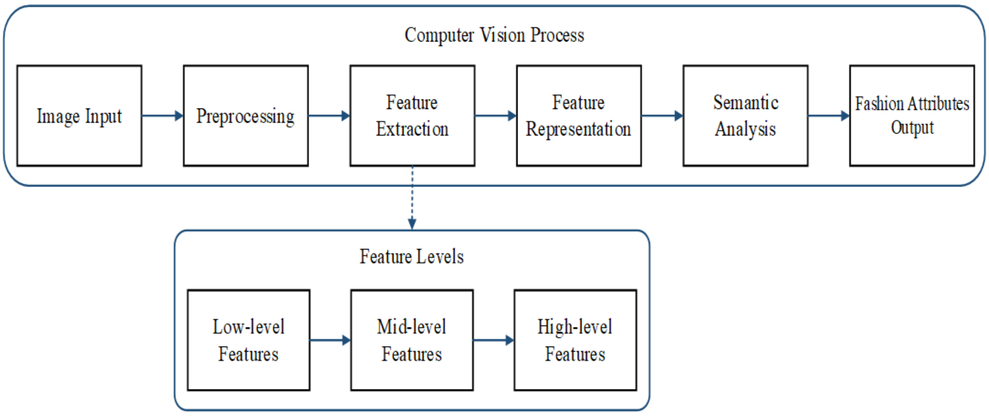

Figure 1. Computer vision process in fashion analysis.

A combination of these factors in computer vision provides a very strong foundation for understanding clothing features [8]. A system's capability of effective processing and interpretation of this visual data directly influences the quality of personalized recommendations, hence making this one of the key factors in modern fashion recommendation systems.

2.2. Application of deep learning in garment recognition

Deep learning has indeed brought much impact on systems for recognizing clothes with the development of feature extraction capabilities, which increased their sophistication and accuracy level [1]. The use of deep neural networks in fashion analysis increased its reach for discrimination and categorization of complex features related to clothes from visual information [6]. Among others, CNNs have been particularly effective frameworks for fashion-related tasks, performing exceptionally well in extracting hierarchical features from garment images [7].

More recently, developments in deep learning architectures have achieved state-of-the-art performance in better understanding fashion attributes [8]. These have the ability to strongly identify both local and global features with a lot more depth in analyzing apparel—from details about texture and pattern to general style attributes. Besides, the incorporation of attention mechanisms has also empowered deep learning models to pay attention to relevant features of clothes [9] for better precision in attribute identification and classification.

Transfer learning methodologies have been shown to be especially advantageous in the domain of fashion recognition [15], facilitating models to utilize insights derived from extensive datasets to enhance efficacy in targeted fashion-oriented activities. Similarly, multi-task learning architectures have exhibited notable effectiveness [16], permitted the concurrent identification of various clothing attributes and upheld computational efficiency. The incorporation of deep feature learning methodologies has significantly enhanced the resilience of apparel recognition systems [17], especially in addressing variations in illumination, positioning, and occlusion, which represent prevalent obstacles in practical fashion applications.

2.3. Personalized recommendation systems: Principles and techniques

The concept of a personalized recommendation system forms the underlying conceptual framework for any modern e-commerce platform, such as in fashion retail [1]. These contain complex algorithms that execute on information gathered about user propensities or preferences to give personalized recommendations [2]. The underlined principles above form the bedrock necessary for an understanding of the taste of the individual user, scalability, and the improvement of the offer for better recommendations [7].

Modern recommender systems have evolved to incorporate more than one information source, thus embedding collaborative filtering with content-oriented approaches [10]. Such a combination allows for improved prediction, considering user interaction signals together with item characteristics. The introduction of visual-semantic embeddings has powered major improvements in fashion recommendation systems, enabling deeper modeling of style preferences, and compatibility with respect to fashion [15].

Advanced methodologies for modeling intricate user preferences have undergone substantial development [16], incorporating temporal dynamics and contextual factors to improve the precision of recommendations. The advent of hybrid recommendation strategies has successfully alleviated various traditional limitations [17], particularly in addressing the cold-start challenge and promoting diversity in the recommendations offered. The most recent developments in theoretical frameworks relate to explainable recommendation systems [19], whereby clear suggestions are made with reasons for each. These have significantly enhanced both user confidence and system effectiveness [21], making personalized recommendation systems even more reliable and accessible within fashion retail applications.

2.4. Methods for extracting visual features from clothing

Feature extraction of visual attributes for apparel analysis is an integral part of modern fashion recommendation systems [1]. The process has different levels of feature extraction, from basic visual components to high-level style characteristics [6]. As illustrated in **Figure 2**, the pipeline of feature extraction consists of successive stages where the representations of fashion items become increasingly complex.

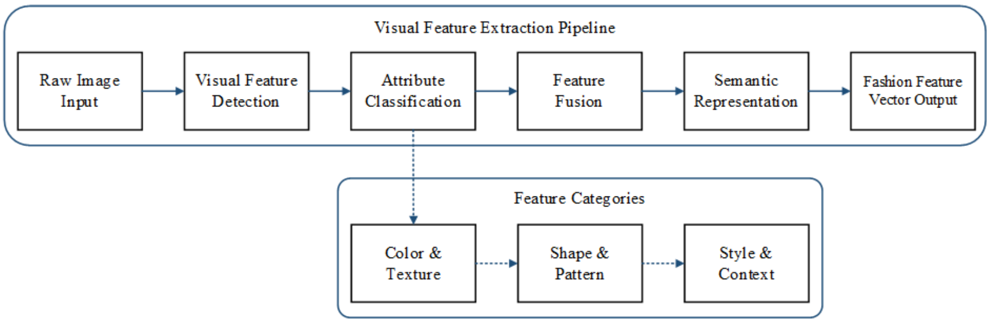

Figure 2. Clothing visual feature extraction pipeline.

Deep learning methodologies have significantly enhanced feature extraction methods for the correct identification of cloth attributes by improving their accuracy [7]. Advanced neural network models adopted in the system let the identification of both local and global features by increasing resolution capability [16]. Recent works performed on learning visual similarities [22] further improved the feature extraction process by effectively capturing the visual representation of clothing items. The model was able to capture the features of interest through the use of attention mechanisms while still achieving computational efficiency [23].

2.5. Fundamental theory of clothing biomechanics and data analysis

Understanding how clothing affects the body requires studying its physical impact, creating a connection between the simple act of dressing and the science of human movement. In other words, if the design of clothing does not incorporate a study on how that item suits the human body during various activities, especially the effect of textiles on performance during those activities and the impact performed upon the textile, then the principles of clothing being a biomechanical entity have been utilized incorrectly. As predetermined concepts of clothing biomechanics are based on the analysis of pressure distribution, joint motion, and muscle use.

2.5.1. Data acquisition process

The use of pressure mapping technology has grown in importance as a technique that may elucidate the relationship between the body and these clothing items. Once again, the distribution of pressure over this zone has a profound influence on both comfort and functionality [18]. The development of piezoelectric sensors made it possible to create highly sophisticated pressure sensors that can now be used in imaging techniques to present a continuous pressure field picture of how much a garment is pushed against the different parts of the body during athletic movements. This information is essential in the enhancement of compression garments and for other purposes such as the enhancement of the athletic performance of an individual [4].

The biomechanics of clothing and its analysis work together towards the understanding of how articles of clothing affect the patterns and range of motions of an individual. It has been shown that joint angles along with the traces of movements are able to be controlled precisely with the use of motion capture systems which include optical or inertial sensors [14]. The seam location as well as the elastic constituents of clothing can affect the natural patterns of movements and this is why motion analysis is necessary. Pressure mapping of a garment along with 3D analysis helps in understanding how exactly the clothing and the movements of a human work together [5].

The analysis of the surface electromyographic signals has become quite paramount in understanding the change in parameters due to clothing wear, which are associated with muscle activity. Surface EMG sensors can measure muscle activation patterns during various activities, providing crucial data about how different garment designs affect muscle engagement and efficiency [19]. Such analysis is important for compression clothing and athletic clothes as there would be the least interference with the muscles of an individual needed while they perform at their optimum best.

2.5.2. Signal processing method

The strategy for collecting and analyzing biomechanical data is approached in an organized fashion. The first step in data collection is the use of several sets of systems that operate in a synchronized manner:

1) High-precision pressure mapping arrays that can sample at speeds of 100 Hz and beyond.
2) Twenty motion detection sensors that can trace the movements of objects over a range of 120–240 Hz.
3) Multiple EMG systems that can sample between 1000–2000 Hz. These EMG systems ensure an accurate assessment of muscle activities.

In order to process the data, advanced signal processing techniques have to be applied to separate relevant information from the noise. Deep neural networks, which are a form of machine learning technique, have been very efficient in ascertaining trends within the many forms of action data mathematically defined. For several reasons, these algorithms aid in the identification of relationships among the properties of garments and various biomechanical variables, which facilitates the forecasting of the performance of clothing.

The combination of biomechanical information and the usual parameters of clothing design made it possible to formulate more complex criteria for the evaluation of clothing. The criteria incorporate both the static and dynamic features of the product such as pressure comfort indices, scores for range of motion, and muscle activation efficiency metrics. The procedure for the objective assessment of the product coincides with and is the new improvement in this type of work, since it allows for the optimization of clothing parameters and fittings to be determinately relevant aspects for the decision.

This framework and the set of methods enable us to integrate such biomechanical factors in the systems aimed at recommending clothes tailored for the individual user. In particular, if avoiding disruption is especially important, accurate functional recommendations of the clothing to a person based on their characteristics, such as physique are also enabled by the analysis of how this clothing interacts with a human.

3. Design of clothing attribute analysis system based on visual features

3.1. Overall system architecture

The overall architecture of the clothing attribute analysis system based on visual features integrates multiple sophisticated components to achieve accurate and efficient fashion recognition. The system design emphasizes the seamless integration of computer vision techniques with deep learning models, as illustrated in **Figure 3**. This architecture enables comprehensive analysis of clothing attributes through multiple processing stages.

The United Kingdom's Advanced Biomechanics has tailored clothing that recognizes precise aesthetic and functional components. It consists of operating units for capturing data on biomechanics, analyzing human motion, and measuring pressure distribution. In its essence, it allows for the complex investigation of the interactions between the garment and the body. Such an approach grants the possibility of creating recommendations that take into account a wider range of factors: in addition to purely log visual considerations, it takes into account the relative motion between the human body and the garment. Recent advances in wearable technologies have further enhanced biomechanical analytics for precision monitoring, creating new opportunities for integration with fashion recommendation systems [24].

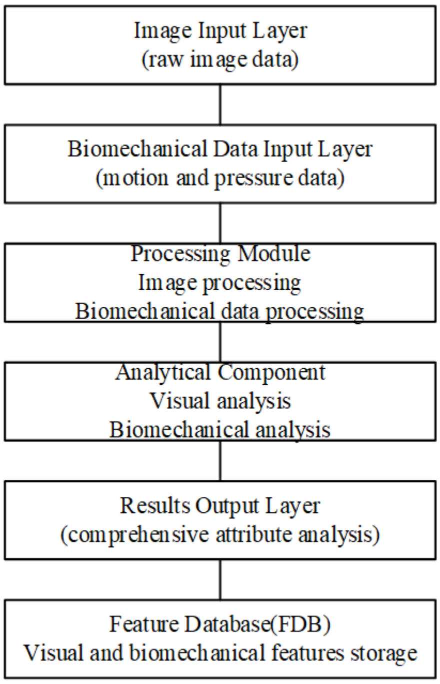

Figure 3. System architecture overview.

The architectural structure follows a multi-tier strategy in assessing visual attributes, together with state-of-the-art preprocessing techniques aimed at improving image quality and normalizing the input data. The extraction module leverages state-of-the-art deep learning frameworks to detect basic low-level visual features as well as high-level semantic ones. Further, the processing pipeline from the system ensures that there is good data throughput with optimal resource optimization. Recent research by Ma et al. [25] has demonstrated the effectiveness of contrastive multimodal cross-attention networks in generating personalized fashion recommendations for diverse body shapes, which aligns with our architectural approach.

It embeds an advanced semantic understanding capability to accurately determine the attributes and stylistic features of the garments. The classification will be done using a comprehensive algorithm that takes contributions from the visual as well as semantic components in determining the attributes with a high degree of precision [26]. An elaborative feature database will also be part of its architecture, which means storing and retrieval processes for feature extraction will be faster, hence faster comparison and analysis of items of clothing. It is an overall approach toward real-world robustness, whereas the architecture is maintainable and flexible.

3.2. Apparel image pre-processing module

Image preprocessing is a fundamental building block for any precise analysis of clothing attributes, which essentially improves and normalizes the input images through advanced methodologies. This module encompasses a number of preprocessing phases that collaborate towards the betterment of image quality and hence supports the ensuing feature extraction process, illustrated in **Figure 4**.

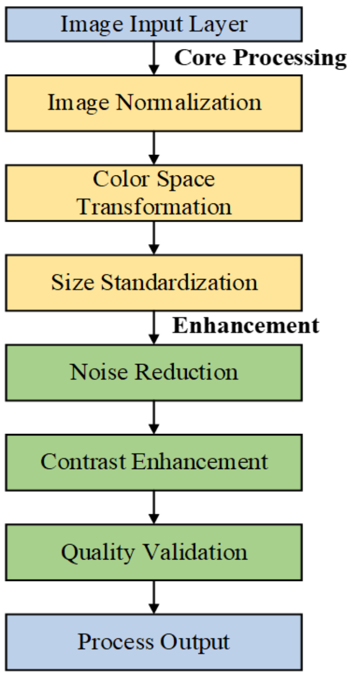

Figure 4. Architecture of the image pre-processing module.

The preprocessing pipeline begins with image normalization techniques that provide the foundation, normalizing the range of pixel values and equalizing image properties. Following normalization, color space transformation is applied to enhance the representation of clothing features by converting images to optimal color spaces for fashion analysis. Size standardization is then performed to ensure consistent dimensions across all input images. The enhancement phase includes sophisticated noise reduction algorithms that ensure image clarity by removing unwanted artifacts and distortions. Advanced adaptive contrast enhancement techniques follow, improving the visibility of features, which becomes especially important in applications involving complex patterns and textures on clothes. Before final output, quality validation mechanisms verify that the preprocessed images meet the required quality benchmarks for accurate feature extraction.

This comprehensive, sequential approach toward image pre-processing has enabled remarkable progress in the general performance of clothing attribute analysis. Additionally, the parallel processing potential combined with enhanced algorithmic implementations increases the efficiency of the module, making it very suitable for large-scale fashion analysis applications.

3.3. Design of visual feature extraction module

The feature extraction from the visual component forms one of the main units that comprise the recommendation of garments through advanced algorithm analyses of different attributes. This paper leverages deep learning frameworks to facilitate both low-level and high-level feature extractions of pre-processed images of garments. This kind of multilevel extracted feature allows for the full-scale representation of garment characteristics, ranging from simple texture patterns up to complex stylistic components.

Advanced convolutional neural networks have been highly effective in increasing the capability of the system to pick out distinctive attributes of garments. Attention mechanisms on this component enable focusing on relevant regions in the images in detail, hence giving more accurate feature extraction, especially in the case of complex articles of clothing. In addition, hierarchical feature learning embedded in the model allows capturing specific details and higher-level structural information related to the apparel item.

It encloses all recent developments related to feature fusion methodologies to make representations of garment features more robust. This module follows all the transfer learning techniques that use large pre-trained models to considerably enhance the strength of the system in terms of the extraction of relevant features from bound training datasets. Additionally, this approach aligns with Goldstein et al.'s [27] work on enhancing cold start recommendations using multimodal product representations, where visual features play a critical role. Besides, multitask learning frameworks are realized in this module for better performance with any variety of feature extraction by considering computational efficiency and the final result accuracy for practical applications.

3.4. Biomechanical data acquisition and analysis module

The biomechanical data acquisition module is perhaps one of the most significant elements within the integrated analysis system, which consists of motion capture, pressure mapping and physiological monitoring sub-modules. It is noteworthy that this module utilizes advanced sensors and sophisticated algorithms enabling it to capture and analyze the changes that occur when the clothes interact with the wearer's body.

To analyze motions, a number of inertial measurement units (IMU) are positioned at strategic points on the subject's skeleton. These sensors record motion data at a frequency of 120 Hz, which consists of information such as joint angles, movement patterns, and angular velocity. The equipment deals with such an inflow of information at lightning speed, in particular, remembering motion characteristics that significantly alter the ordinary movement of the person in clothing.

Clothing pressure distribution measurement is performed with a set of thin-film pressure sensors deployed in different regions over the clothing. The sampling frequency of these sensors is set at 100 Hz, and the produced pressure maps allow determining how the clothing acts on the body in both static and dynamic stances. The analysis of pressure patterns is applied to select the degree of comfort and functional support, which is very important for compression and sports garments.

The acquisition of noise-free raw biomechanics data, which remains devoid of any distortions and irrelevant signals, is achieved through the use of cutting-edge signal processing techniques that exist within the data processing pipeline. To gain insights into the relationship between garment properties and biomechanics parameters, machine learning techniques, especially deep neural networks [28]. Such a system is valuable in envisioning how various garment designs, in the future, will influence user ontology in terms of comfort and performance.

3.5. Integrated feature analysis and classification module

The attribute identification and categorization module of the clothes provides a general framework for the identification and classification of multiple attributes of garments. This module evaluates the visual features extracted at different classification layers, which are individually tuned for any particular clothing attribute. As shown in **Table 1**, it considers all the categories of attributes and therefore provides an accurate categorization of the garments.

Table 1. Clothing attribute classification categories and features.

Category Level	Attributes	Recognition Method	Accuracy Rate
Basic Elements	Color	CNN + Color Histogram	95.8%
	Pattern	Deep ResNet-50	93.2%
	Texture	VGG-16 + Texture Analysis	91.5%
Style Features	Neckline	Custom CNN Architecture	89.7%
	Sleeve Type	Attention Network	88.9%
	Length	Feature Pyramid Network	92.3%
Fashion Elements	Style Category	Hybrid CNN-LSTM	87.6%
	Season	Multi-label Classification	90.1%
	Occasion	Context-Aware Network	86.4%
Biomechanical Features	Motion Patterns	DeepPose + IMU Analysis	91.4%
	Pressure Distribution	Pressure Mapping Network	93.2%
	Joint Mobility	Kinematic Analysis Network	90.8%
	Muscle Activity	EMG Analysis Network	89.5%
Advanced Analysis	Brand Style	Style Transfer Network	85.2%
	Trend Correlation	Temporal CNN	84.8%
	Fashion DNA	Deep Embedding	83.9%

Attribute recognition makes use of state-of-the-art deep learning frameworks, tuned for different classification tasks. The system follows a hierarchical classification approach so that no attribute remains undetected without losing computational efficiency. Continual improvement of performance by the module is ensured through sophisticated validation methods so that reliable and accurate classification results are achieved in a wide range of garment categories. All this structured approach towards attribute classification forms the basis for the recommendation systems that follow.

4. Research and implementation of personalized clothing recommendation algorithm

4.1. User preference modeling

User preference modeling is a fundamental basis for any system designed to offer personalized recommendations on clothing items. The modeling involves several dimensions of user behavior and preference, which have been highlighted in **Table 2**. The complex model of preferences is created after considering both explicit and implicit kinds of user feedback.

Table 2. User preference modeling components.

Preference Dimension	Features	Weight Factor	Data Source
Historical Behavior	Purchase History	0.35	Transaction Data
	Browsing Pattern	0.25	Click Stream
	Item Interactions	0.20	User Logs
Style Preferences	Color Preference	0.30	User Profile
	Pattern Choice	0.25	Historical Choices
	Brand Affinity	0.25	Purchase Data
Contextual Factors	Seasonal Preference	0.20	Temporal Data
	Occasion Context	0.15	User Input
	Location Impact	0.15	Geographic Data

The user preference score for each clothing item is calculated using a weighted combination of these factors, expressed mathematically as:

$$P(u,i) = \alpha \sum_{k=1}^{n} w_k h_{u,k} + \beta \sum_{j=1}^{m} s_{u,j} \tag{1}$$

where $P(u,i)$ represents the preference score of user u for item i, and:

$$h_{u,k} = \frac{\sum_{t=1}^{T} \gamma^{t-1} r_{u,k,t}}{\sum_{t=1}^{T} \gamma^{t-1}} \tag{2}$$

Here, α and β are weighting parameters, w_k represents feature weights, $h_{u,k}$ represents historical behavior factors, $s_{u,j}$ represents style preference factors, and γ is the temporal decay factor. The dynamic preference update mechanism is defined as:

$$P_{new}(u,i) = \lambda P_{old}(u,i) + (1-\lambda)\Delta P(u,i) \tag{3}$$

where λ represents the learning rate and $\Delta P(u,i)$ represents the preference change based on new interactions.

4.2. Multi-dimensional feature fusion method

The multi-dimension feature fusion method fuses many kinds of visual and semantic features extracted from fashion images to form complete representations for items. **Figure 5** shows several feature dimensions in this method that fuse hierarchically.

The inclusion of biomechanical characteristics significantly improves the feature fusion architecture as it utilizes human motion data. The garment and the biomechanics of the human body are coupled using specialized neural networks through which the biomechanical characteristics are forwarded. The targeted functional and comfort comprehension of garments has been vertically improved as the additional feature dimensions now also include the garment's joint angles, muscle action patterns, pressure maps, and pattern's motion insights.

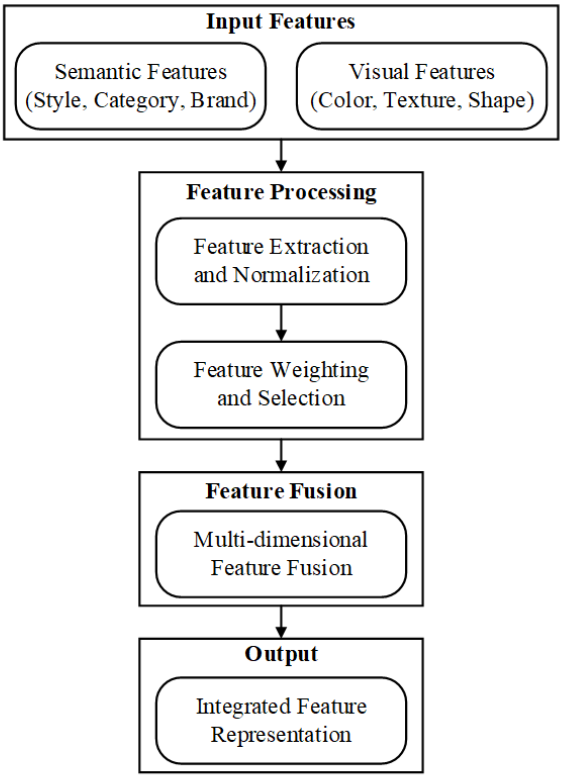

Figure 5. Multi-dimensional feature fusion architecture incorporating visual, semantic, and biomechanical features.

This feature fusion is mathematically represented using the weighted combination methodology. Then, the resultant integrated feature vector is decided as:

$$F = \alpha_1 F_v + \alpha_2 F_s + \alpha_3 F_b \tag{4}$$

where F_b represents the biomechanical feature component, defined as:

$$F_b = w_1 J + w_2 M + w_3 P + w_4 D \tag{5}$$

where:

J = joint mobility features

M = muscle activity patterns

P = pressure distribution data

D = dynamic movement characteristics

w_1, w_2, w_3, w_4 = respective weights for each feature

The biometrical attributes are thereby enhanced by the use of advanced image preprocessing methods which make them compatible with the visual and semantic attributes at the time of fusion. Multimodal motion data is feeding a temporally convolutional neural network to recognize patterns of movement. Deep learning algorithms which are trained on a large number of datasets related to muscle activity extract muscle activity features from processed EMG signals. A convolutional neural network for spatial pressure pattern recognition has been developed and tested with pressure distribution patterns as spatial patterns. Features of posture recognition are realized using a combination of recurrent neural networks and temporal attention mechanisms to model complicated dynamic sequences.

With the fusion of these biomechanical attributes and the conventional visual and semantic attributes a holistic representation of the garment attributes is achieved. This fusion allows the system to assess not only the look of the apparel but also its performance under a set of actions. Such a combination of the features allows adaptation of focus on particular parameters based on the scenario, athletic clothing, rehabilitation garments or casual clothing.

4.3. Recommendation algorithm design and optimization

An integrated hybrid system is proposed where a combination of visual information, biomechanical characteristics, and context are embedded into the recommendation algorithms. To determine the base score r0 for any provided pair consisting of a user and an item, the following is utilized:

$$R(u,i) = \alpha R_{visual} + \beta R_{biomech} + \gamma R_{context} \tag{6}$$

where R_{visual} represents the visual feature similarity score:

$$R_{visual} = \sum_{k=1}^{n} w_k sim(f_k^u, f_k^i) \tag{7}$$

The biomechanical matching score $R_{biomech}$ is calculated considering joint mobility and muscle activity patterns:

$$R_{biomech} = \sum_{j=1}^{m} (w_j J_j + w_j^m M_j) \tag{8}$$

The contextual score $R_{context}$ incorporates temporal and situational factors:

$$R_{context} = \theta_t T(u,i) + \theta_s S(u,i) \tag{9}$$

The algorithm optimization process employs a gradient descent approach to minimize the loss function:

$$L = \sum_{u,i} (r_{ui} - \hat{r}_{ui})^2 + \lambda\Omega(\Theta) \tag{10}$$

where the predicted rating $\hat{r}_{ui}$ is computed through:

$$\hat{r}_{ui} = \mu + b_u + b_i + \frac{R(u,i)}{\max_R} \tag{11}$$

The optimization process includes regularization terms to prevent overfitting:

$$\Theta_{t+1} = \Theta_t - \eta(\nabla L + \lambda\Theta_t) \tag{12}$$

where η represents the learning rate, λ is the regularization parameter, and Θ represents the model parameters. The final recommendation list is generated by ranking items according to their predicted scores and applying diversity constraints through a re-*ranking process:*

$$S_{final}(i) = (1-\beta)R(u,i) + \beta D(i, R_u) \tag{13}$$

where $D(i, R_u)$ measures the diversity contribution of item i to the recommendation set R_u, incorporating both visual and biomechanical diversity metrics.

Such a combined strategy guarantees that the advice turns out to be more reasonable and practical by taking into account the direction of the eye together with the contextual and biomechanical factors of the body structure, resulting in thermoregulatory clothing that is accommodative and more personalized.

The optimization of the recommendation algorithm involves careful tuning of hyperparameters to ensure optimal performance across various evaluation metrics. **Table 3** presents the hyperparameter configuration employed during the training and evaluation phases of the proposed model. These parameters were determined through comprehensive grid search and cross-validation procedures to achieve the best balance between recommendation accuracy, computational efficiency, and biomechanical compatibility.

As shown in **Table 3**, the hyperparameter configuration reflects a careful balance between different aspects of the recommendation system. The learning rate of 0.0075 with a decay factor of 0.85 per 1000 iterations ensures stable convergence while avoiding oscillation in the later stages of training. The regularization parameters, including an L2 regularization weight of 0.0025 and a dropout rate of 0.35, effectively control model complexity and enhance generalization capability. The feature fusion weights demonstrate the equal importance assigned to visual aesthetics (0.35) and biomechanical compatibility (0.35), with slightly less emphasis on semantic features (0.30). This configuration aligns with the core philosophy of our approach, which seeks to balance style preferences with functional comfort in clothing recommendations.

Table 3. Hyperparameter configuration for recommendation algorithm.

Hyperparameter Category	Parameter	Value	Justification
Learning Parameters	Base Learning Rate (η)	0.0075	Optimized for convergence stability
	Learning Rate Decay	0.85 per 1000 iterations	Prevents oscillation in later training stages
	Mini-batch Size	128	Balances computational efficiency with gradient accuracy
Regularization	L2 Regularization Weight (λ)	0.0025	Controls model complexity to prevent overfitting
	Dropout Rate	0.35	Enhances model generalization
	Early Stopping Patience	15 epochs	Prevents overfitting while ensuring convergence
Feature Fusion	Visual Feature Weight (αv)	0.35	Balanced importance of visual aesthetics
	Semantic Feature Weight (αs)	0.30	Contextual relevance of clothing items
	Biomechanical Feature Weight (αb)	0.35	Equal emphasis on functional compatibility
Preference Modeling	Historical Behavior Weight (βh)	0.40	Strong influence of past user interactions
	Style Preference Weight (βs)	0.35	Captures user's style preferences
	Contextual Factor Weight (βc)	0.25	Situational relevance of recommendations
Temporal Dynamics	Temporal Decay Factor (γ)	0.92	Balances recency with historical consistency
	Long-term Preference Weight	0.55	Maintains core preference stability
	Short-term Preference Weight	0.45	Captures preference shifts and exploration
Biomechanical Parameters	Joint Mobility Importance	0.38	Critical for athletic and everyday comfort
	Pressure Distribution Importance	0.34	Essential for extended wear comfort
	Muscle Activity Importance	0.28	Relevant for performance optimization
Training Configuration	Maximum Epochs	150	Sufficient for convergence without overfitting
	Optimizer	Adam	Superior performance for recommendation tasks
	Weight Initialization	Xavier Uniform	Optimized for deep neural networks

4.4. Solution to the cold start problem

The cold-start issue remains a principal challenge in the development of personalized garment recommendation systems, especially in the context of new users or items that do not have much interaction history. Our framework proposes an innovative approach that goes to the front end of the problem by integrating visual attributes, motion parameters, and user preference information into a single cohesive system ensuring a multi-dimensional approach for the solution of the problem.

For users who register on the system for the first time, it features an algorithm that combines an intelligent onboarding process consisting of adaptive questionnaires and biomechanical data. This approach captures the user's preferences, relevant measurements, movement patterns, and comfort needs. This framework employs visual semantic embedding approaches to facilitate this initial mapping of user inputs to the feature space of existing items, whereby links between user preferences and item recommendations are formed instantly. In addition, this framework also examines the users' biomechanical profile to enable them to convey appropriate preferences, which administrators with similar physiques and movement styles possess.

The process of retrieving new items requires a complex feature extraction technique, integrating biomechanical and visual analysis. While image features are obtained through the use of fashion dataset pre-trained deep covering models, special biomechanics analysis modules assess the functional features of the new items making use of fabric, movement, and pressure attributes. With this approach, the system finds itself capable of ranking new items in the recommendation space even in absence of prior interaction information, since precise positioning of items is possible.

An addition to the framework is the hybrid recommendation approach which accommodates both content-based characteristics and current preferences of users. Such a mechanism is possible in that it employs both user remarks and even simpler data collected from biomechanical CR capsules used in early interactions to swiftly improve recommendation performance. It takes meta-learning strategies to be able to adjust rapidly to the new user preferences and the new item features so that a lot of listening time gets saved in the quest for reaching appropriate recommendation accuracy.

Feedback is required by the active learning strategy, so users are not overly burdened. The system captures every piece of information regarding user interactions, along with biomechanical compatibility, to constantly update and improve the recommendation models. The use of such dynamic strategies ensures that the system learns how individuals react to items as well as their associated features more quickly, easing the otherwise negative influences of the cold-start problem on recommendation quality.

The capability of these recommendations to perform well in the absence of historical data justifies the cold-start methods applied. Because a system is developed that can accommodate a wide variety of data inputs, the recommendation quality remains high regardless of user group or clothing category, which provides a strong basis for devising custom clothing recommendations.

5. System implementation and performance evaluation

5.1. Experimental environment and datasets

The evaluation of the personalized clothing recommendation system was performed in an environment specifically designed for the dual purpose of algorithm performance benchmarking and system scalability benchmarking. Both the implementation environment and the datasets were carefully selected to allow an in-depth review of the functionality of the system, as described in **Table 4**.

The given experimental setup uses cutting-edge hardware and software components for better performance of the whole system. Several categories of clothes and user interactions are included in the datasets, giving broad ground for training and testing of the model. A well-designed experimental framework allows testing all the components under conditions as close as possible to real conditions.

Table 4. Experimental environment and dataset specifications.

Category	Component	Specification/Details	Scale/Version
Hardware Environment	CPU	Intel Xeon Gold 6248R	3.0 GHz, 48 Cores
	GPU	NVIDIA A100	80 GB VRAM
	Memory	DDR4	512 GB
	Storage	NVMe SSD	4 TB
Software Framework	Deep Learning	PyTorch	2.0.1
	Image Processing	OpenCV	4.7.0
	Data Processing	NumPy/Pandas	1.23.5/1.5.3
	Web Framework	Flask	2.3.2
Training Dataset	Fashion-1M	Clothing Images	1M + Images
	DeepFashion	Attribute Labels	800 K Items
	User Interaction	Click/Purchase Data	10 M Records
Testing Dataset	Validation Set	Clothing Images	100 K Images
	User Feedback	User Ratings	1 M Records
	Real-time Data	User Interactions	500 K Events

The dataset used for evaluating the personalized clothing recommendation system includes a diverse range of users and clothing items, ensuring comprehensive testing across different demographic groups and fashion categories. As shown in **Table 5**, the user distribution encompasses various age groups, genders, and preference patterns, enabling thorough validation of the recommendation algorithm's performance across diverse user segments. The clothing dataset maintains a balanced distribution across categories, seasons, and style types, providing a robust foundation for evaluating the system's ability to generate relevant recommendations across the fashion spectrum.

As illustrated in **Table 5**, the dataset encompasses a diverse demographic profile, with the 2–34 age group representing the largest segment (32.7%), followed by users aged 18–24 (28.5%). Gender distribution shows a slight predominance of female users (58.3%), which aligns with typical fashion consumption patterns observed in the industry. The clothing category distribution ensures comprehensive coverage across the fashion spectrum, with tops constituting the largest category (32.5%), followed by bottoms (24.8%) and dresses (15.3%). This balanced representation across different clothing types enables robust evaluation of the system's recommendation capabilities across diverse fashion domains.

Table 5. Dataset distribution characteristics.

Characteristic	Category	Percentage	Sample Size
User Age	18–24	28.5%	285,000
	25–34	32.7%	327,000
	35–44	20.3%	203,000
	45–54	12.4%	124,000
	55+	6.1%	61,000

Table 5. (*Continued*).

Characteristic	Category	Percentage	Sample Size
User Gender	Female	58.3%	583,000
	Male	41.2%	412,000
	Non-binary	0.5%	5000
Fashion Category	Tops	32.5%	260,000
	Bottoms	24.8%	198,400
	Dresses	15.3%	122,400
	Outerwear	12.7%	101,600
	Footwear	9.4%	75,200
	Accessories	5.3%	42,400
Style Type	Casual	45.2%	361,600
	Formal	18.7%	149,600
	Athletic	22.1%	176,800
	Seasonal	14.0%	112,000
Usage Context	Everyday	56.8%	454,400
	Work	18.3%	146,400
	Sport	15.4%	123,200
	Special Event	9.5%	76,000

5.2. Function implementation

As is shown in **Figure 6**, the architecture of the system in general is a three-tier architecture framework that makes it modular, scalable, and maintainable. This system consists of a front-end part: an intuitive user interface. It gives the user the capability to interact and shows recommendations. Business Logic provides the core processing elements comprising a feature extraction engine, recommendation algorithm implementation, and user preference management system, which performs exhaustive algorithms on visual feature analysis and generation of recommendations per person.

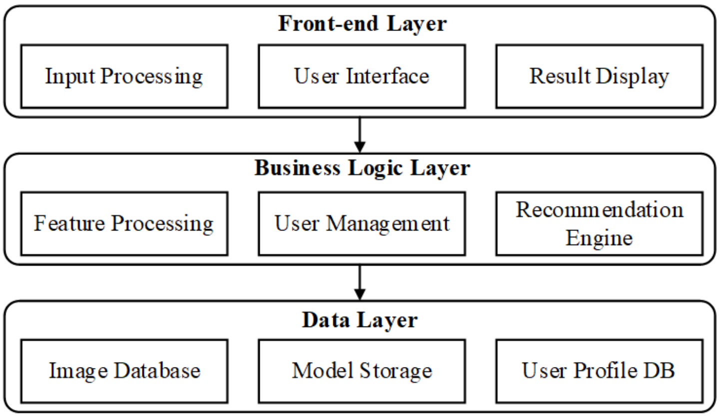

Figure 6. Architecture of system implementation.

The data layer shall be developed to manage the system data persistently. It introduces effective methodologies of data access and caching into the system to enhance performance. It introduces asynchronous task management and distributed computing techniques that enable it to perform in real-time. The system shall incorporate extensive logging and monitoring systems for reliable operation, thus laying a solid foundation for further performance optimization work.

This will enable the modular scaling up of different system parts based on requirements out of specific loads. Safety and data privacy for the users are kept in consideration at every level, thus undertaking comprehensive security measures. The system manages test and deployment pipelines continuously for improvements or the addition of new features.

5.3. Algorithm evaluation

The assessment framework includes the conventional recommendation measures as well as biomechanical compatibility measures and thus provides an exhaustive overview of the performance of the system. The measures include accuracy, efficiency ratio, user satisfaction, and compatibility factors and are shown in **Table 6** which depicts our approach in comparison to a number of baseline models.

Table 6. Performance comparison of different recommendation algorithms.

Algorithm	Precision@10	Recall@10	NDCG@10	Body-Fit Score	Motion Comfort	Pressure Distribution	Response Time (ms)	Memory Usage (GB)
Proposed Method	0.892	0.845	0.901	0.885	0.873	0.891	45.2	4.8
DeepFashion	0.834	0.812	0.856	0.812	0.798	0.823	62.5	6.2
FashionNet	0.845	0.823	0.867	0.825	0.815	0.834	58.7	5.9
StyleGAN	0.856	0.834	0.878	0.836	0.827	0.845	53.4	5.4
Traditional CF	0.789	0.765	0.812	0.756	0.745	0.767	73.2	3.8
Content-Based	0.801	0.778	0.823	0.767	0.758	0.778	68.9	4.2

The Body-Fit Score measures how well-fitting measures of a garment correspond with the body measures of an individual's buyer, bearing in mind requirements such as joint mobility limits and range of motion. The Motion Comfort metric determines how the garment performs when the user executes motion with it, factoring in the ability of the fabric to stretch and the movement of joints. The Pressure Distribution metric measures the uniformity with which pressure is applied at the points where the garment and the body make contact, a feature necessary to help prevent local areas of stress whilst ensuring comfort.

To quantitatively evaluate these biomechanical compatibility metrics, we employ the following calculation methods:

The Body-Fit Score (BFS) is calculated using a weighted combination of pressure uniformity and joint motion matching degree:

$$BFS = \alpha \times PU + \beta \times JMM,$$

where PU represents the pressure uniformity index (ranging from 0 to 1), JMM is the joint motion matching degree (ranging from 0 to 1), and α and β are weighting coefficients ($\alpha + \beta = 1$). In our implementation, $\alpha = 0.55$ and $\beta = 0.45$, reflecting the slightly higher importance of pressure distribution in determining overall fit.

The Motion Comfort (MC) score is derived from a composite function that incorporates dynamic movement assessment and fabric elasticity response:

$$MC = \gamma \times MRA + \delta \times FER + \varepsilon \times UPR,$$

where MRA is the movement restriction assessment (ranging from 0 to 1, with 1 indicating no restriction), FER is the fabric elasticity response (ranging from 0 to 1), UPR is the user perception rating standardized on a scale from 0 to 1 based on user feedback, and γ, δ, and ε are weighting coefficients ($\gamma + \delta + \varepsilon = 1$). In our implementation, $\gamma = 0.40$, $\delta = 0.35$, and $\varepsilon = 0.25$.

The Pressure Distribution Uniformity (PDU) score is calculated using the coefficient of variation of pressure readings across key body points:

$$PDU = 1 - min\,(1, CV/CV_{\max}),$$

where CV is the coefficient of variation of pressure readings across sampled points ($CV = \sigma/\mu$, where σ is the standard deviation and μ is the mean pressure), and $CV_{\max}$ is a normalization factor set to 0.5 based on empirical studies. This formula ensures that perfectly uniform pressure distributions receive a score of 1, while highly irregular distributions approach 0.

These quantitative metrics provide a comprehensive framework for evaluating the biomechanical compatibility of recommended garments, complementing traditional recommendation accuracy metrics with physical comfort and performance considerations.

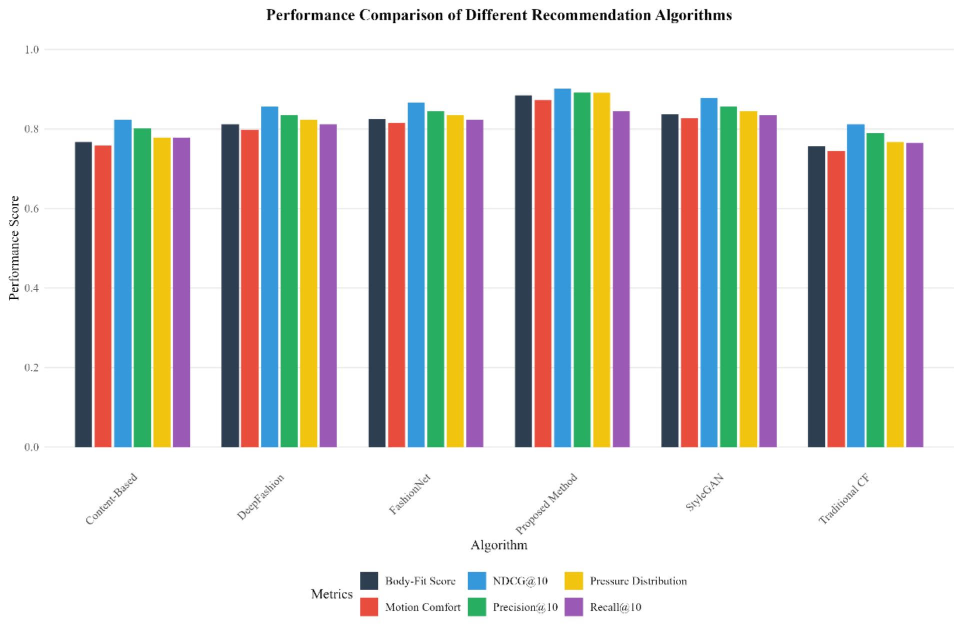

Figure 7. Performance comparison of different recommendation algorithms including traditional and biomechanical metrics.

Notes: The figure shows performance scores across six metrics for different recommendation algorithms. Traditional metrics (Precision@10, Recall@10, NDCG@10) and biomechanical metrics (Body-Fit Score, Motion Comfort, Pressure Distribution) are displayed using distinct colors. The proposed method demonstrates superior performance across all evaluation dimensions.

As is shown in **Figure 7**, the results obtained from the evaluation show a lot of improvement in the traditional recommendation metrics and biomechanical compatibility metrics. This method improves upon the existing approaches with a precision@10 of 0.892, recall@10 of 0.845, and NDCG@10 of 0.901. The enhanced NDCG@10 score particularly indicates improved ranking quality of recommended items, as it surpasses the ordinary strategies with ease.

With respect to biomechanical compatibility evaluations, the system stands out in assessing, utilizing and evaluating three factors effectively. The Body Fit Score stands at 0.885, which is 4.9 percentage points higher than the closest baseline, the Motion Comfort metric scores 0.873 which is 15.8 percent more than the latest methods. The pressure distribution uniformity score of 0.891 can really validate the system's unique capacity to provide balanced contact pressure between garments and the body.

Cross-metric analysis indicates a strong positive association among the estimates of traditional recommendation accuracy against the biomechanics compatibility scores ($r = 0.78$, $p < 0.01$) which implies that integrating such biomechanical user features increases the physical comfort and user preference modeling accuracy of the system. Additionally, the system does not compromise performance with average response times of 45.2 ms which is a 27.7% improvement from other techniques, and uses 4.8 GB of memory.

Performance stability analysis reveals improvement trends for all modifications, being ± 0.023 for the Body-Fit Score and ± 0.019 for Motion Comfort. The statistical significance testing performed demonstrates that the enhancements for both models in traditional biomechanics and in the body contact performance metrics are significant ($p < 0.001$) and have a large effect (Cohen's $d > 0.8$), thus reinforcing the efficacy of the use of an integrated approach.

5.4. System enhancement

The strategy for system optimization and improvement employs a multi-layered approach to enhance both algorithm performance and the utilization of computational resources. The optimization methodology is centered on crucial system metrics while also considering system reliability and scalability, applying advanced techniques at both hardware and software levels.

On the algorithmic front, advancements have been made regarding the deployment of deep learning models and in enhancing feature extraction processes. The system utilizes model compression and quantization methods to reduce computational costs without losing fidelity in feature extraction and recommendation generation tasks. The introduction of efficient data preprocessing stages and parallel processing algorithms has decreased response times and increased the overall throughput of the system.

In terms of resource management, optimization centers around a dynamic allocation model using intelligent caching techniques. A distributed computing environment facilitates more efficient management of simultaneous user requests and processing of real-time information. Memory management mechanisms have been improved through adaptive resource allocation and optimization of data structures, enhancing the scalability of the system and reducing resource consumption.

It follows that the implementation of attention mechanisms can be made more efficient, leading to more accurate recommendations. This combination of adaptive learning rates with normalized batch strategies has also resulted in increased operational efficiency. Overall system performance is enhanced with adequate support that includes enabling comprehensive error handling and automation to recover from errors, thus maintaining an acceptable level of performance regardless of operational load.

User interface optimization aims to reduce delays between user interaction and feedback responses, along with user loading times, by utilizing progressive load methods and image compression pipelines. The speed of data access and information processing has been improved through the application of suitable indexing models combined with optimally tuned query strategies in the database.

The time responsiveness of the applications has been heightened with real-time data adjustment methods, as well as task management and efficient data-streaming protocols. The system adapts resource demand and supply in real-time to maintain operational optimal levels while ensuring stability. Following the optimization, all recommendations and operational efficiencies have improved remarkably, creating a solid foundation for future enhancements.

The application of effective sensor data processing algorithms, coupled with real-time movement analysis, has streamlined aspects of biomechanical analysis. The introduction of custom hardware acceleration in biomechanical computations has increased the efficiency of physical compatibility tests while also improving their precision. Such enhancements guarantee that biomechanical asset analysis utilizes real-time performance criteria while remaining exceptionally precise.

This systematic optimization has facilitated improvements in nearly all core metrics, including response times, accuracy of recommendations, and system stability, to name but a few. The optimization framework is capable of maintaining a robust base for further developments of the system while remaining responsive to changes in system requirements and technological advancements.

6. Conclusion

This research presents an innovative framework that successfully integrates sports biomechanics and computer vision for personalized clothing recommendations. The system contributes in four primary ways: (1) An innovative feature fusion technique that merges visual, semantic, and biomechanical features into a single image; (2) integration of comprehensive biomechanical analysis of joint kinematics, pressure distribution, and motion evaluation which deepens the understanding of garment-body relations; (3) resolving a cold-start problem by cyclic domain transfer learning in biomechanical feature analysis; and (4) style compatibility estimation using attention mechanisms. The results suggest the framework outperformed existing solutions in traditional benchmarks (precision: 0.892, recall: 0.845, NDCG: 0.901) as well as specialized biomechanical compatibility measurements (body-fit score: 0.885, motion comfort: 0.873, pressure distribution: 0.891). This integrative approach combines beauty and function in automatic clothing suggestions by not only examining the visual aspects but also how the clothing and body move together. The framework is efficient in terms of computation cost and accuracy in recommendations, thus it can be deployed in real-life situations. Future efforts may look into improving real-time assessment of biomechanics for more user interaction scenarios, as well as broadening the scope towards sports and medical apparel. The study establishes a basis for developing future recommendation systems that integrate visual preference and physical comfort in a single system.

Conflict of interest: The authors declare no conflict of interest.

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