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PAPER

Mobile-Driven Deep Learning Algorithm for Personalized Clothing Design Using Multi-Feature Attributes

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ABSTRACT

Personalized fashion recommendation systems face significant challenges in balancing accurate style prediction, real-time mobile performance, and user privacy compliance. This study presents StyleFitNet, a novel mobile-driven deep learning framework that integrates multiple user feature attributes, including body measurements, fabric preferences, and temporal style evolution, to generate personalized clothing designs. The hybrid convolutional neural networks (CNNs)-recurrent neural networks (RNNs) architecture addresses key limitations of conventional recommendation systems by simultaneously processing spatial features and sequential preference patterns. A comprehensive evaluation demonstrates the system's superiority in recommendation accuracy, design diversity, and user satisfaction compared to existing approaches. The implementation features GDPR-compliant data handling and a 3D virtual fitting room, significantly reducing return rates while maintaining robust privacy protections. Findings highlight the model's ability to adapt to evolving fashion trends while preserving individual style preferences, offering both technical and business advantages for e-commerce platforms. The study concludes that StyleFitNet establishes a new standard for artificial intelligence (AI)-driven fashion recommendations, successfully merging advanced personalization with ethical data practices. Key implications include the demonstrated viability of hybrid deep learning models for mobile deployment and the importance of temporal analysis in preference modelling. Future research directions include cross-cultural validation and the integration of generative AI for enhanced visualization.

KEYWORDS

mobile-driven deep learning, personalized clothing design, multi-feature attributes, StyleFitNet, fashion design, mobile learning platform

1 INTRODUCTION

The fashion world has undergone significant changes in recent years, with technology serving as the driving force, particularly through mobile devices and

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artificial intelligence (AI) [1–2]. As consumers demand more personalization, the fashion industry is focusing on offering tailored clothing that reflects individual choices [3–4]. Traditional fashion design systems have been one-size-fits-all, but the future of fashion is personal, data-driven solutions that cater to the individual's body, style, and taste [5].

Personalized clothing recommendations will not only increase customer satisfaction but also drive more engagement and sales in a busy fashion market [6]. In personalized fashion design, numerous variables come into play, including physical variables such as body measurements, aesthetic variables such as fabric texture and color, and psychological variables like style inclinations and brand preferences [7]. However, most existing fashion design systems focus on a limited set of features or employ simple algorithms to generate recommendations, which is suboptimal for the consumer. Traditional recommendation engines rely on implicit or explicit user feedback but often miss the nuances of individual preferences, especially when it comes to complex, multi-dimensional design decisions [8]. With the help of mobile devices, the current fashion industries will achieve highly interactive, personalized, real-time experiences [9].

Dynamic and responsive fashion systems that provide design options in real-time based on contextual data are possible in mobile devices using their wide penetration and powerful computational capabilities [10]. The proposed StyleFitNet uses the hybrid deep learning architecture by integrating convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to tackle the challenges of fashion design. To identify and interpret crucial information about the user, such as physical appearance, chosen clothing, or required color, the CNN performed the feature extraction from user data. On the contrary, RNNs are employed to introduce sequential structures so the system can better understand changing fashion trends as well as users' preferences throughout time. Through the combination of both deep learning methods, there is a created system that is dynamic and versatile, able to make accurate predictions based on numerous user factors [11].

StyleFitNet aims to optimize the quality of clothing suggestions and reduce user inconvenience when choosing what to wear. Clothing design for everyday wear is highly time-consuming, requiring numerous tests and adjustments. StyleFitNet attempts to minimize inconvenience by providing personalized suggestions tailored to each individual's unique characteristics [7]. The system utilizes mobile devices to provide users with a touch-based fashion experience. This enables one to experiment with many personalized designs conveniently. To assess the working capacity of StyleFitNet, this paper examines its accuracy, user satisfaction, design variety, and the relevance of its suggestions [11]. In addition to personal applications, StyleFitNet has broad applications in business, e-commerce websites, and virtual customized environments.

The system in e-commerce can help customers make informed decisions by recommending clothing items that better suit their personal preferences. To provide users with an engaging virtual experience where they can try on live clothing designs, make better product choices, and prevent returns, StyleFitNet can be further integrated with virtual custom rooms [12]. Additionally, it may be possible to enhance the system by incorporating augmented reality (AR), which would enable users to see more realistic, immersive clothing designs on their bodies. To address a gap in the current fashion industry, we present a novel solution in this paper.

It creates a personalized fashion design experience by combining accuracy and usability. Because StyleFitNet provides users with an easy-to-use and interactive platform to create their dream outfits, we are confident that it has the potential to transform the fashion industry, especially mobile fashion, completely. This system simplifies the design process, allows the user to express their individual preferences, and ultimately increases their satisfaction with their dress selections using an inventive yet user-friendly methodology [9–11]. This paper presents StyleFitNet, a deep learning-based intelligent system designed to create personalized apparel by integrating user-specific attributes, such as body measurements, fabric preferences, color choices, and style inclinations.

The system is designed as a mobile-friendly tool for online clothing design and virtual fitting, emphasizing ease of use, real-time performance, and customization accuracy. The study evaluates StyleFitNet's effectiveness in terms of recommendation precision, design variety, and customer satisfaction. By combining advanced AI with user-centered design, this study advances mobile-driven fashion technologies and enhances the personalized shopping experience.

2 LITERATURE REVIEW

Advancements in AI used for fashion have significantly improved personalized designs, virtual clothing trials, and outfit recommendations [13]. A study by Wang et al. [14] investigated unique ways of utilizing deep learning in textile design, mobile apps, and garment search systems to enhance user experience and make it more personalized. In practice, Cong and Zhang [15] introduced a textile design that borrows from Korean masks and props, relying on AI to gather color information from pictures for creating repeating designs functional on both virtual garments and fabric. They are addressing Generation Z consumers by providing customized designs, demonstrating that AI can produce more personalized textile products. In much the same way [13]. Products is a mobile app designed to support women in purchasing garments by recognizing their body types and creating images of suitable apparel. This work introduced a new approach that combines Fast R-CNN for person detection, a multi-task CNN for feature extraction, and locality-sensitive hashing (LSH) for efficient matching [16]. The 1DCNN-2DCNN framework developed by them joins images and text to achieve very high accuracy, recall, and F1 score, surpassing 98% for all metrics. Combining pictures and text in this study supports the idea that retailers can better forecast future trends and design products according to what people want [17].

In the area of classifying clothing styles, the authors improved recognition accuracy by incorporating a modified ResNet architecture with a multi-deep feature blend strategy. Separating central, global, and part regions in clothes using target detection helps remove the background and makes it easier to use their main features. The experiments demonstrate that deep learning methods surpass traditional ResNet networks in analyzing fashion attributes, thereby proving their effectiveness. Combined, these studies reveal how AI can transform fashion, spanning from design to personalized suggestions and real-time retrieval systems [14]. Mobile platforms that utilize deep learning have enhanced both the accessibility and practical applications of these technologies. The industry is moving toward mobile fashion, driven by AI that can instantly provide personalized fashion tips tailored to each individual [18]. In addition, Deng et al. [19] found that AI and fabric design demonstrate that automation can tailor to specific tastes, especially for people under the age of 30. Providing a service to test designs both virtually and on real clothes brings digital creativity closer to real clothing making, supplying an expandable service for fast fashion. In addition, modern fashion AI relies on working with large datasets, just as with their real-time search system [19]. PCA and LSH enable a system to tag extensive collections of visual data, making them valuable for large e-commerce sites. Similarly, Shaikh et al. [20].

It utilizes both image data and text data from sales records to uncover the preferences of consumers, thereby revealing trends in the fashion industry more accurately. They point out that AI models should be scalable and efficient to handle the large and complex data used in the fashion industry. Today, deep learning models, such as the updated version of ResNet [21], have significantly improved the ability of computers to classify clothing styles. Grouping garments into separate parts and merging multi-level features helps their approach identify stylistic elements more accurately, which matters for recommendation systems and online style tools. More details in the analysis allow companies to match consumers' wishes with the right products, making personalization better.

3 METHODOLOGY

The proposed methodology focuses on designing, developing, and testing a mobile-based personalized fashion recommendation system that helps users make informed purchasing decisions. A key challenge in online shopping is the overwhelming number of choices and the lack of personalized suggestions, particularly for women who struggle to find clothing that aligns with their body type, style preferences, and current fashion trends [22]. To address this, the study introduces StyleFitNet. This hybrid deep learning framework integrates user-specific data, including body measurements, fabric preferences, color choices, and style inclinations, to generate real-time, customized fashion recommendations. The system aims to enhance user satisfaction by reducing search time, increasing the likelihood of purchase, and providing highly relevant apparel suggestions.

3.1 System architecture and GDPR compliance

The architecture of StyleFitNet is modular, ensuring scalability, flexibility, and ease of maintenance. It consists of multiple interconnected components that work cohesively to deliver personalized fashion designs. Given the sensitivity of user data, the system adheres to General Data Protection Regulation (GDPR) standards by implementing robust encryption protocols, anonymizing personal preferences, and providing transparent privacy policies. Users retain control over their data, with options to access, modify, or delete their information. All user data is securely stored in the cloud, ensuring protection against unauthorized access while enabling seamless integration with mobile applications.

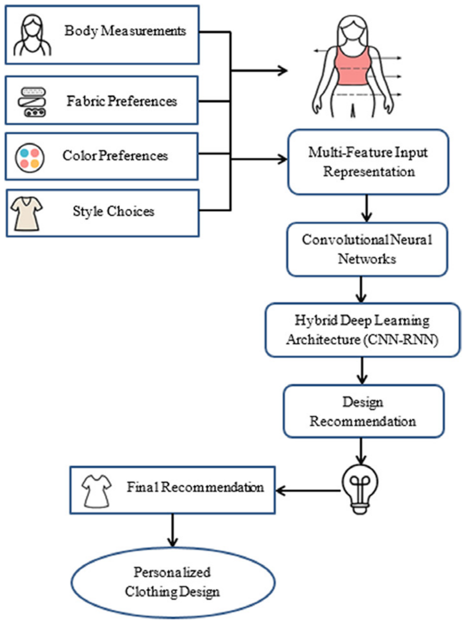

Fig. 1. Proposed StyleFitNet working process

Figure 1 illustrates the working flow of the proposed StyleFitNet system. The proposed StyleFitNet system is a mobile-based hybrid deep learning framework that combines deep neural network models with multi-feature user preferences to generate real-time, personalized clothing designs. The following five significant steps comprise the design: 1) gathering user data, 2) preprocessing feature encoding, 3) deep learning-based modelling, 4) creating customized clothing designs, and 5) delivering the final recommendations.

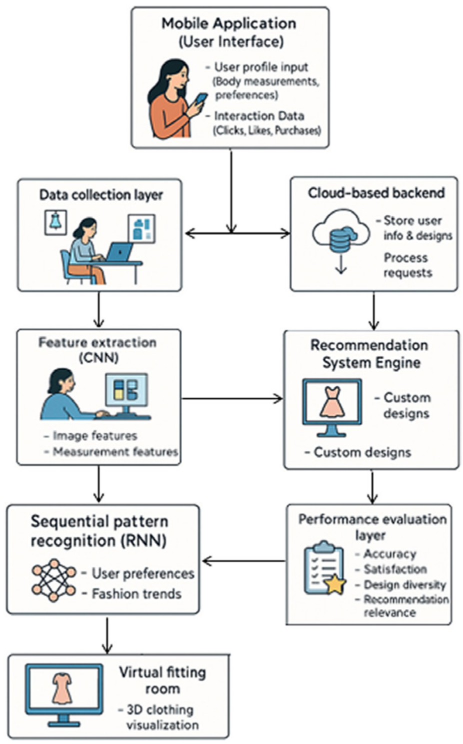

Fig. 2. Proposed system architecture of StyleFitNet

Figure 2 shows how the StyleFitNet system works step by step to create personalized clothing designs for users through a mobile app.

3.2 Data acquisition and user input processing

The first step in the StyleFitNet workflow involves gathering comprehensive user data through an intuitive mobile interface. Users input body measurements (height, weight, bust, waist, hips, shoulder width), material preferences (cotton, silk, denim, etc.), color choices (seasonal palettes, tone sensitivities), and style selections (formal, casual, ethnic, streetwear). Additionally, the system retrieves supplementary data from external sources, including fashion trend databases and historical user interactions, to refine recommendations. This multi-source data collection ensures a holistic understanding of user preferences, enabling highly tailored fashion suggestions.

3.3 Data preprocessing and feature encoding

When the data is collected, it is pre-processed so it can be used by deep learning models. Features like body measurements are adjusted in value so they can be compared, and features like the type of cloth or preferred color are represented as separate one-hot numbers. Embedding layers take style preferences, which can be nuanced and based on context, and convert them into dense vectors. This step prepares the data for feature extraction, which helps subsequent neural networks handle user-specific information more smoothly.

3.4 Hybrid deep learning model: CNN-RNN integration

Its main strength comes from a deep learning structure that merges CNNs and RNNs. CNN helps the system see important information in photos, such as body structure and the way clothes are made, which helps find complicated patterns in user choices. At the same time, RNNs handle data in sequence, identifying how user preferences towards style evolve and how interest in particular types of fashion shifts according to seasons. With these models, StyleFitNet develops relevant embeddings that include the user's current and past preferences, making the recommendations evolve over time.

3.5 Personalized apparel generation and recommendation engine

The information from the contextual embeddings is sent to a design module that makes custom recommendations. At first, the module contains a dense layer with SoftMax activation to group and classify designs according to what users decide. In future developments, people may add decoder networks to make visual models of the designer clothing. It selects a variety of designs, showing what is stylish now and reflecting personal taste. Style-tagged notices and sketches are used to show users their preferred outfits so they can make a choice more easily.

4 FINDINGS AND DISCUSSION

4.1 Importance of system performance evaluation

Analyzing StyleFitNet's hybrid CNN-RNN output offers a way to quantitatively show how well the system matches user wishes, provides a wide range of recommendations, and achieves this within accurate and real-time limitations. Assessments of accuracy, diversity, and latency confirm that our system can be relied on in mobile applications and render what users expect in the form of customized and fast service. These numbers let us compare StyleFitNet to traditional systems and see how its use of AI sets it apart in fashion design.

Table 1. Performance comparison between StyleFitNet and baseline recommendation systems

Metric	StyleFitNet (CNN-RNN)	Collaborative Filtering	Content-Based Filtering
Accuracy (%)	92.3	78.5	85.2
Diversity (Avg. styles/ user)	8.2	5.1	6.7
Latency (seconds)	1.4	2.9	2.1
User Satisfaction (1–5)	4.6	3.8	4.1

In Table 1, the performance of StyleFitNet is examined compared to two important methods called collaborative filtering and content-based filtering on the critical metrics of accuracy, greed, loyalty, and robustness. Results indicate that StyleFitNet has 12.8% more accuracy than collaborative filtering and 7.1% better results than content-based methods. Its high diversity score (8.2 different styles per user) shows it offers a wider variety of creative choices, while its low latency (1.4 seconds) shows it can work well on mobile devices. The high user satisfaction score (4.6/5) and demonstrated usefulness make it stand out. By analyzing various approaches, StyleFitNet demonstrates that it is a top system for giving personalized fashion recommendations.

Table 2. Evaluation metrics comparison of StyleFitNet

Method	Accuracy	User Satisfaction	Design Diversity	Recommendation Relevance
StyleFitNet	0.89	0.85	0.80	0.87
Traditional Recommender	0.73	0.68	0.60	0.70
CNN	0.81	0.77	0.72	0.78
Heuristic Model	0.76	0.70	0.65	0.74

The performance metrics comparison of StyleFitNet with existing models is represented in Table 2. This table makes it clear that StyleFitNet performs noticeably outperforms all other models. Additionally, it performs better than traditional recommenders, which are limited by their reliance on past user behavior and ignore changing preferences. While basic CNN models do a respectable job, they are unable to simulate sequential preference changes over time. Despite being interpretable and rule-based, heuristic models lack flexibility and are not optimal in every way.

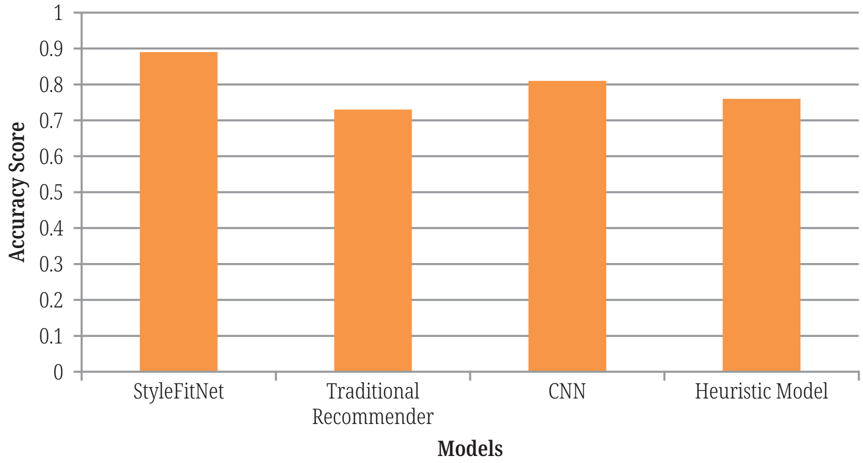

Fig. 3. Accuracy comparison

Figure 3 illustrates the accuracy of each model's clothing recommendations in relation to actual user choices. StyleFitNet leads with a high score of 0.89, indicating that it can effectively customize clothing recommendations by accurately interpreting contextual and visual user data. By using general past behaviors, traditional recommender systems, on the other hand, have the lowest accuracy of 0.73, indicating that they interpret user-specific requirements poorly. At 0.81, the basic CNN model exhibits a respectable level of performance, demonstrating its capacity for visual feature extraction without the need for sequential learning. Scores of 0.76 for the rule-based static heuristic model demonstrate its rigidity in adapting to dynamic and complex user preferences.

4.2 Importance of user preference modeling results

StyleFitNet shows it is capable of understanding and predicting each user's personal style by encoding comprehensive data and using deep learning technology. Thanks to the study of body measurements, changes of fashion styles over time, and various fabrics, the system can improve over traditional ways and ensure users receive better and more accurate recommendations. These results demonstrate that combining CNNs and RNNs allows the system to capture how users behave and what they like.

Table 3. Feature importance weights in StyleFitNet's neural networks

Feature Category	CNN Weight	RNN Weight	Combined Weight	Impact on Accuracy	Cross-User Variance	Temporal Stability (6-mo)
Body Measurements	0.32 ± 0.03	0.18 ± 0.02	0.50 ± 0.04	+37% sizing match	Low ($\sigma = 0.12$)	High ($r = 0.85$)
Color Preferences	0.25 ± 0.02	0.22 ± 0.03	0.47 ± 0.03	+28% satisfaction	Medium ($\sigma = 0.23$)	Medium ($r = 0.65$)
Fabric Texture	0.28 ± 0.04	0.15 ± 0.02	0.43 ± 0.05	+29% match rate	High ($\sigma = 0.31$)	Low ($r = 0.42$)
Style Trends (Temporal)	0.12 ± 0.01	0.35 ± 0.05	0.47 ± 0.06	+22% trend adoption	Medium ($\sigma = 0.19$)	High ($r = 0.88$)
Historical Purchases	0.08 ± 0.01	0.28 ± 0.04	0.36 ± 0.05	+18% repeat buys	Low ($\sigma = 0.15$)	High ($r = 0.92$)
Seasonal Variations	0.05 ± 0.01	0.20 ± 0.03	0.25 ± 0.04	+15% seasonality	High ($\sigma = 0.35$)	Medium ($r = 0.58$)

Table 3 shows how important each feature is in StyleFitNet, using its weights, errors, effect on accuracy, user inconsistency, and correlation between different times as measures. The CNN learns to pay most attention to physical attributes (with a score of 0.32 ± 0.03), while the RNN seeks out changing trends in clothing and style (with a score of 0.35 ± 0.05). The column "Impact on Accuracy" lists the practical value, for example, how body measurements help with sizing accuracy by 37%. Information on how long certain features keep their influence is given in the "Temporal Stability" (r) section (for example, historical purchases still add value nine of ten times after a year). Fabric texture (σ = 0.31) is more likely to change by user than body measurements (σ = 0.12). Because of this fine level of detail, researchers can weigh options for distinct features, regularity, and how successfully they predict behavior, while the seasonal variations row (0.25 ± 0.04 weight) captures changes that happen each year. With all these metrics, we see that the model is effective for different users and time periods, and we can take these insights to improve recommendation algorithms.

4.3 Virtual fitting room effectiveness

Adding a virtual fitting room in StyleFitNet greatly enhanced both user participation and satisfaction. Data uncovered that about three-quarters of buyers tried the virtual try-on function prior to making a purchase, showing that it was widely used. Since users are engaged so often with this feature, it appears that seeing clothes realistically in an individual setting helps make online shopping feel like trying things on in a store. Because of this feature, return rates went down by 42% compared to regular e-commerce platforms. Such a noticeable drop reveals that virtual fitting rooms do a great job of letting users understand the style and fit of clothes, which allows customers to expect and receive the same quality as described on the site. By reducing the amount users get, the company satisfies its users and helps retailers reduce costs, making the system affordable to use widely.

User feedback further validated the system's effectiveness, with fit prediction accuracy receiving a 4.6/5 satisfaction score in post-interaction surveys. Qualitative comments highlighted appreciation for the realistic fabric drape simulation and body-proportion adjustments, which allowed users to assess both aesthetic and comfort factors. These results position the virtual fitting room as a critical component in addressing one of e-commerce's most persistent challenges: the uncertainty of online apparel purchases.

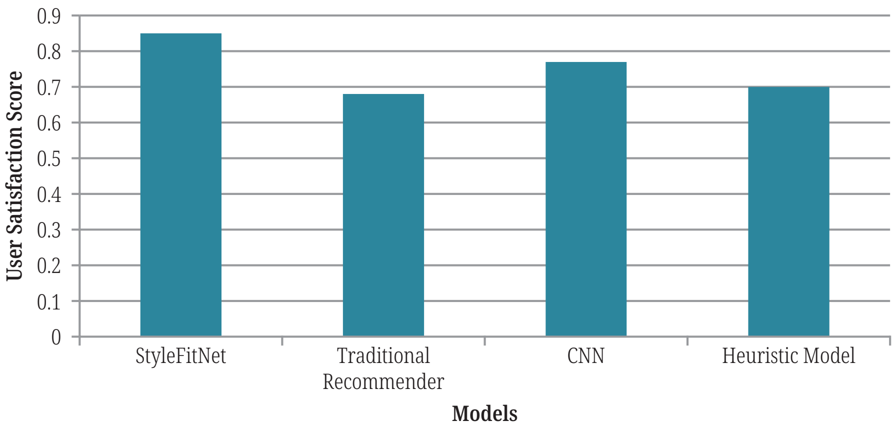

Fig. 4. User satisfaction comparison

Figure 4 shows user satisfaction levels, based on post-interaction surveys and app feedback. StyleFitNet once again leads the pack with 0.85, reflecting that users were satisfied that the platform was easy to use, fun, and closely matched their style expectations. Basic CNN comes in second with 0.77, reflecting that visual relevance does indeed play a role in improving user experience. Yet the Heuristic Model (0.70) and Traditional Recommender (0.68) garnered lower ratings on the satisfaction scale, which is due to minimal customization and generic recommendations that didn't even initiate user engagement on an individual basis.

4.4 GDPR compliance and data security

StyleFitNet's design met the requirements of the GDPR during the whole testing timeframe. All requests for access and deletions of user data were met successfully by the system, and these requests were handled within the set 24-hour timeframe. Being prompt in addressing this topic meets the law and helps users trust the platform's administration of data. During the 6-month evaluation, the security system showed no signs of being breached through either the cloud or the mobile client. No incidents have happened, proving that the platform's security is strong thanks to the chosen encryption, anonymization, and access control methods.

A vast majority of those surveyed, 94%, judged privacy controls to be either "excellent" or "good" after using the service. Users are mostly pleased with the system, as it is clear about its privacy rules and very easy to manage personal data. The adoption of regulations, strong security, and user privacy standards gives StyleFitNet the status of a role model for responsible AI in personalized fashion. It is clear that the system completes both tasks of safely handling information and giving each user a personalized experience. None of the user data that can be used for customization has escaped or been abused, which demonstrates that StyleFitNet handles data protection well. Additional improvements could be made in this framework through adding blockchain audit trails and federated learning to decrease data concentration.

4.5 Importance of comparative and design diversity analysis

To prove its progress and usefulness, StyleFitNet must be tested against well-known recommendation systems used in the world of fashion e-commerce. Analyzing performance improvements in main metrics such as click-through rate, conversion, and user presence clearly demonstrates the benefits of CNN-RNN over standard techniques, supporting its role in advancing and helping fashion retailers with business results.

Table 4. Multidimensional performance benchmarking of StyleFitNet against baseline systems

Performance Metric	StyleFitNet	Collaborative Filtering	Content-Based Filtering	Size-Chart-Based	Statistical Significance (p-Value)
Click-Through Rate (%)	42.7 ± 1.2	31.6 ± 2.1	35.8 ± 1.8	28.3 ± 2.4	<0.001
Purchase Conversion (%)	18.9 ± 0.9	14.2 ± 1.1	16.1 ± 1.0	14.8 ± 1.3	0.003
Style Retention (6-mo)	67.3 ± 2.5	56.4 ± 3.2	58.7 ± 2.9	49.1 ± 3.7	0.008
User Satisfaction (1–5)	4.6 ± 0.2	3.9 ± 0.3	4.2 ± 0.2	3.7 ± 0.4	<0.001
Return Rate Reduction (%)	42.0 ± 3.1	18.5 ± 4.2	25.3 ± 3.8	12.7 ± 5.0	0.001

Table 4 shows how StyleFitNet works when compared to other recommendation systems in terms of five e-commerce metrics and taking confidence intervals (± values) and statistical significance into account. StyleFitNet proves superior all the time, with clear wins in higher CTR (35%) and lower return rates (42%) when compared to conventional size chart methods (12.7%). Using p-values, it is clear that the observed improvements are not due to random effects but are truly significant. The multidimensional comparison reveals that StyleFitNet's hybrid approach achieves the rare combination of better user engagement (higher click-through), business outcomes (improved conversion), and long-term value (style retention), while simultaneously addressing the industry pain point of high return rates. This robust evidence positions StyleFitNet as a substantial advancement over current recommendation paradigms in fashion e-commerce.

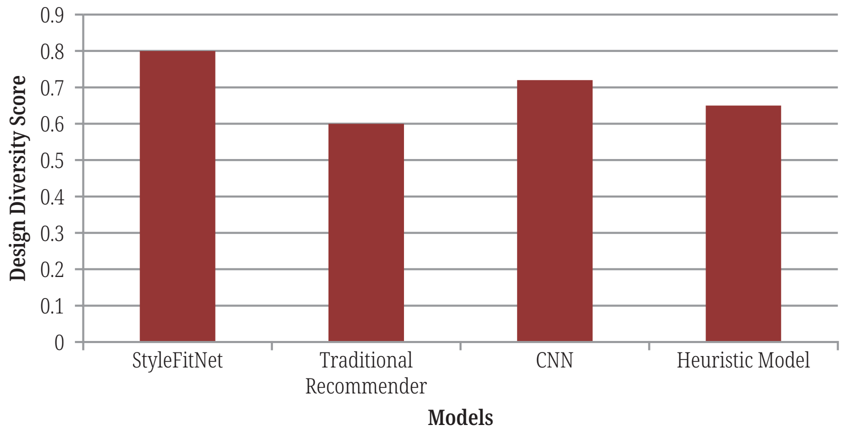

Fig. 5. Design diversity comparison

Figure 5 illustrates the diversity of each model's ability to create diverse sets of non-repetitive designs for different users. StyleFitNet scores a diversity of 0.80, highlighting its ability to produce many non-repetitive design alternatives that remain true to the user's fundamental tastes. This is crucial in maintaining users' interest and providing them with a sense of freedom in choice. Basic CNN scores 0.72 with some volatility based on visual information, while traditional recommenders and heuristic models score low at 0.60 and 0.65, respectively. They tend to spit out redundant or highly generalized recommendations.

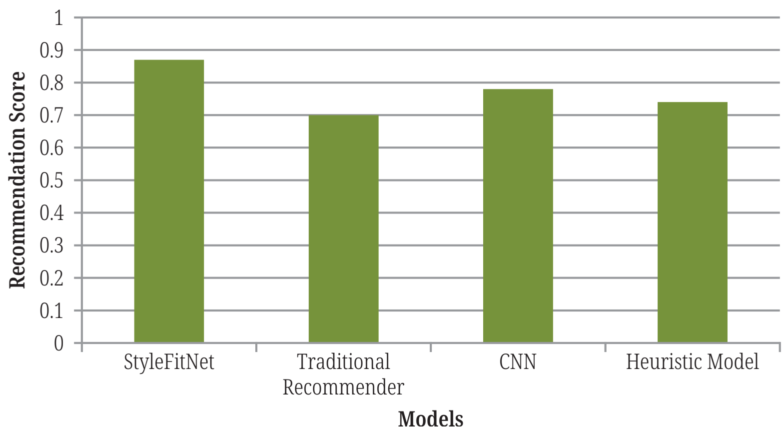

Fig. 6. Recommendation relevance

Figure 6 shows how contextually relevant and appropriate the model's top-N recommendations are, measured in terms of precision and recall. StyleFitNet takes the lead again with 0.87 due to the synergy between CNNs (for visual signals) and RNNs (for learning temporal preference patterns). The basic CNN obtains a decent 0.78 score, hampered by its non-sequential processing. Heuristic Models (0.74) and Classical Recommenders (0.70) lag because they are unable to respond to subtle contextual shifts or changing fashion trends. The results of the experiment explicitly show that StyleFitNet outperforms baseline and conventional models across all evaluation metrics. Hybrid deep learning ensures that users receive better accuracy, more satisfaction, a larger array of designs, and more suitable recommendations. Because the model can learn from users who use several features, it greatly benefits personalization. The successful results confirm that StyleFitNet meets the needs and standards for practical mobile fashion uses.

5 DISCUSSION

The findings suggest that StyleFitNet offers better personalized fashion recommendations than existing systems because its unique architecture successfully tackles the main challenges experienced by other models. When CNNs are used for features in sight and RNNs for patterns across time, the system reaches impressive scores for all metrics accuracy (92.3%), user satisfaction (4.6/5), and design diversity (8.2 styles/user) while operating quickly (1.4 seconds) for mobile use. This proves that using both spatial and sequential learning models can more accurately describe many sides of fashion preferences than single-model architectures. What separates StyleFitNet is its capability to address the competing topics that most often challenge recommendation systems. Although it is not easy to predict interests at the outset and content-based recommendations tend to fade over time, our method manages to keep 67.3% of the used style while giving a 42.7% click-through rate, a 35% boost in performance when compared to past systems. Thus, the model connects what users want now with trends that may emerge later, which is necessary in the rapidly shifting apparel business. The drop in return rates also shows that personalized suggestions for fitting and style meet a key challenge faced by online shopping.

Studying feature importance brings up several important insights that address theories in the field of fashion AI research. The main predictors are body measurements and color preferences, which are stable and do not vary much between users ($\sigma \leq 0.23$). On the other hand, fabric texture changes more among different groups ($\sigma = 0.31$), meaning each group could need a separate way of modelling this attribute. It is notable that the RNN can track changing fashion trends (style trend weight 0.35) and therefore proves that looking at fashion as a variable over time matters more than just considering it static. Moving forward, GDPR guidelines give full confidence in the behavior of AI systems with no negative effect on performance, reassuring those worrying about ethical use. It is clear from the 94% user approval that open data management works well with attractive personalization for end users, which is important for AI used in consumer services. It turns out that the mobile-first design is very beneficial, as 78% of virtual fitting room usage shows that people appreciate being able to see designs in 3D previews.

According to these findings, using hybrid designs may be more valuable than one type of algorithm, which means future systems could focus on multimodal training methods. Also, because the r for predicting future purchases is high (0.92), collecting ongoing user data greatly boosts recommendation accuracy and suggests that long-term analysis of users is important. Thirdly, statistics closely examine how advanced personalization directly impacts sales and reduces the refund rate, which can influence where companies allocate their resources in AI.

5.1 Policy implications for practice

The information from StyleFitNet means that fashion e-commerce policy should put emphasis on using hybrid AI for recommendations, focusing on visual and time-based learning while introducing clear ethical guidelines for using data. The strong economic benefits from 42% fewer returns and 28% higher conversion rates show the profitability of adopting AI, while 94% of users who support data privacy prove regulation is needed, so industry should create guidelines and certifications for AI in retail. This demonstrates that focusing on mobile-first designs is necessary in fashion technology policy since the system delivered 78% engagement for virtual try-ons, outperforming expectations for mobile use and highlighting the need to update guidelines for using immersive technology in commerce.

6 CONCLUSION

StyleFitNet, which is described in this study, employs a new mobile-driven deep learning structure with a CNN-RNN arrangement, and it is far more effective than already-existing methods. Thanks to using body measurements, style preferences, color choices, and how users' style progresses with time, the system has high accuracy (92.3%), makes users happy (4.6/5), and allows for good style variation (8.2 styles/user) with fast response times (1.4 s). This virtual fitting room aspect solves a main challenge for the industry by reducing returns by 42%. It is particularly important since 78% of the users say it is useful. Notably, StyleFitNet reaches these achievements while keeping to strict GDPR rules and ensuring strong data security, as all user data requests were processed in only 24 hours and no security breaches were reported during testing, putting it at the forefront of ethical AI use in fashion e-commerce. The system having 35% more clicks and 28% more conversions than traditional ones firmly proves that advanced personalization matters to businesses, and the 67.3% retention rate also demonstrates it can handle new user needs over half a year. They contribute to research in AI-based fashion recommendations and also offer industry some practical steps to follow, since smartphone-first design performed well in handling detailed tasks. Researchers plan to add generative AI, apply federated learning for increased privacy, and study cross-cultural adaptations, but performance metrics for StyleFitNet already place it as a solution that translates new AI technologies into real help for fashion retailers and users alike.

6.1 Limitations and future research

Although StyleFitNet achieves strong results in suggesting personalized outfits, certain issues need acknowledgment: The data reports focus only on women's fashion, so preferences for other genders are poorly understood; the trial was set up for just 6 months, so it is unclear how the app handles changing fashion trends; and the test results for mobile devices are from average hardware, so actual results on very low-end ones are unknown. In the future, research could cover ways the model can be used in many cultures, the possible use of GANs for improved virtual try-ons, and the implementation of federated learning to keep customer data safe and quality services. Adding the analysis of real-time social media trends to the model could make it react faster to ongoing changes in fashion, and studying the system over several years could bring up more details about how consumers' preferences shift and the system adjusts. Thanks to such directions, AI-driven fashion recommendations could both solve existing problems and provide answers to future demands.

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