

AI-BASED OUTFIT RECOMMENDATION SYSTEM

Yaswanthraj S¹, Mohithra S², Pavithra Kumar Nadar³, Shakthi S⁴

¹ Assistant professor, Department of Computer Science and Engineering (CYBER SECURITY) Sri Shakthi Institute of Engineering and Technology Coimbatore, India

² 2nd year student, Department of Computer Science and Engineering (CYBER SECURITY) Sri Shakthi Institute of Engineering and Technology Coimbatore, India

³ 2nd year student, Department of Computer Science and Engineering (CYBER SECURITY) Sri Shakthi Institute of Engineering and Technology Coimbatore, India

⁴ 2nd year student, Department of Computer Science and Engineering (CYBER SECURITY) Sri Shakthi Institute of Engineering and Technology Coimbatore, India

Abstract - The expanding request for personalized online shopping encounters has driven the advancement of cleverly proposal frameworks custom-made to person client inclinations. Within the design industry, a customized approach to styling proposals upgrades client fulfillment and shopping effectiveness by proposing outfits and adornments that adjust with each user's interesting characteristics, such as body shape, skin tone, stature, and fashion inclinations. In any case, conveying precise personalized proposals is challenging due to the subjective and complex nature of design, requiring a nuanced understanding and versatile reactions to client needs. This paper presents a comprehensive clothing proposal framework utilizing progressed calculations to prepare client inputs and produce custom-made equip proposals. Through a user-friendly web interface, the framework captures key individual properties and employments a generative proposal show to supply real-time, personalized styling counsel. Clients are guided on a styling travel that considers their particular highlights, making a difference them investigate closet choices that best complement their appearance. The stage coordinating item joins for a streamlined shopping involvement and utilizes MongoDB for secure information capacity, guaranteeing strong administration and assurance of client data. This approach upgrades client fulfillment and addresses the specialized challenges of personalized design proposals within the advancing online retail scene.

Key Words: content filtering, collaborative filtering, KNN, neural networks, AI-based RSs.

1. INTRODUCTION

In today's progressively computerized world, personalized online shopping has ended up a foundation of client fulfillment, particularly in businesses like design, where shoppers anticipate suggestions that reflect their one of a kind fashion, body sort,

and individual inclinations. A well-designed clothing proposal framework can altogether upgrade the shopping encounter by advertising custom-made equip proposals that adjust with a user's particular body characteristics, skin tone, stature, and tasteful tastes. Be that as it may, building such a framework presents a few challenges due to the exceedingly subjective and differing nature of individual mold. Planning a stage that can decipher these person contrasts precisely whereas giving significant and noteworthy proposals could be a complex but basic task.

Traditional design proposal frameworks have by and large depended on inactive, rule-based approaches, which offer constrained adaptability when it comes to adjusting to differing client needs. These frameworks regularly need the capacity to handle nuanced individual characteristics and inclinations, driving to less personalized and now and then unimportant recommendations. Later progressions in manufactured insights (AI) and

machine learning, be that as it may, have empowered the improvement of more energetic, data-driven recommendation[1] models that can way better cater to particular client inputs. This move has made it conceivable to construct proposal systems[2] that can provide personalized encounters in real-time, with distant more prominent precision and relevance.

This paper aims to use a generative AI[5] model to make a clothing suggestion framework able of translating detailed user inputs such as physical characteristics, fashion inclinations, and stylistic tastes, to supply customized furnish proposals. By analyzing these person traits, the framework can create personalized suggestions that improve a user's appearance and offer assistance them find styles that are adjusted with their interesting inclinations. The objective is to offer a more agreeable and custom fitted shopping encounter where clients can investigate equip alternatives suited to their body shape and individual style.

To guarantee both security and smooth operation, the framework coordinating a vigorous backend system, utilizing a

mongoDB database for effective information administration and capacity. The stage prioritizes information security and shields touchy client data. Also, the framework streamlines the shopping involvement by giving coordinate item joins, permitting clients to easily purchase suggested things. This approach points to address the developing request for personalized shopping instruments within the mold industry, giving a consistent, secure, and versatile arrangement that upgrades client fulfillment and advances a more locks in shopping travel.

2. LITERATURE SURVEY

Matthew O. Ayemowa, Roliana Ibrahim, Muhammad Murad Khan look at how Recommender Frameworks (RSs) have ended up basic devices over different applications, conveying personalized substance to upgrade client encounters. Whereas conventional AI-based RSs are broadly executed, they confront challenges such as information sparsity, cold begin issues, and restricted differences. As of late, generative AI has altogether progressed RS capabilities, with major stages like Netflix, Spotify and amazon embracing models such as generative ill-disposed Arrange (GANs), Variational Autoencoders (VAEs), and autoencoders to move forward suggestions. This survey compares conventional and generative AI-based RSs by analyzing 52 considers distributed from 2019 to 2024 over six major online libraries. Discoveries uncover that generative models beat conventional strategies, with MovieLens and Amazon datasets as often as possible utilized, and Review and RMSE as common assessment measurements. The survey offers bits of knowledge into the procedures, models, and measurements utilized in generative AI-based RSs, highlighting patterns, challenges, and future inquire about directions.

Amarjeet Rawat, Sunil Ghildiyal, Anil Kumar Dixit, Minakshi Memoria, Rajiv Kumar, Sanjeev Kumar investigate how Recommender Frameworks (RSs) have applications over assorted areas where computerized data is created at a fast pace. These frameworks are basic for sifting huge volumes of computerized information that capture client inclinations, interface, and behavior designs related to items and administrations. With the fast improvement of manufactured insights in zones like computerization, computation, information building, and data recovery, RSs have been significantly improved. Methods such as fluffy rationale, neural systems, common dialect handling, exchange learning, and machine learning are instrumental in progressing the execution and precision of RSs, whereas moreover tending to challenges such as cold begin, information sparsity, protection, and versatility. This paper talks about the formative stages and categories of RSs, as well as the challenges and rising patterns in their construction.

Shaghayegh Shirkhani, Hamam Mokayed, Rajkumar Saini, Murmur Yan Chai examine the special challenges postured by the design industry's differences, volume, and pace, which make it challenging for clients to choose on buys. Not at all like other spaces where Recommender Frameworks (RSs) ordinarily depend on similitude, mold requires a center on compatibility, because it includes coherent styles over clothing things. Additionally, the visual qualities of mold items, which intensely impact proposal calculations, contrast essentially from metadata utilized in other spaces. This writing audit investigates different

Counterfeit Insights (AI) methods as of late connected in mold recommender frameworks, which empower more refined and personalized suggestions than conventional approaches. The progressions in AI have driven to superior bits of knowledge into user-item connections and designs inside statistic, printed, visual, and relevant information. By conducting a comprehensive survey of image-based mold RS inquire about over the past decade, this work points to supply a more profound understanding of the design recommender space, emphasizing the special, nuanced perspectives significant to fashion-specific RS characteristics.

Aminu Dau and Naomie Salim display a precise writing audit (SLR) on profound learning-based recommender frameworks (RSs) pointed at tending to data over-burden in spaces like e-commerce, amusement, and social media. Whereas conventional RS strategies have accomplished significant victory, they still confront issues like cold begin and information sparsity. As of late, profound learning progressions in regions such as Common DialectPreparing (NLP) and picture preparing have driven analysts to coordinated these methods into RSs, improving suggestion quality. Be that as it may, few auxiliary thinks about have synthesized the advance in profound learning-based RSs. This paper is the primary to embrace an SLR particularly for profound learning in RS, giving a organized investigation based on high-quality investigate distributions, taking after standard SLR rules set by Kitchenmen-ham. Through cautious choice and investigation, this audit uncovers that autoencoder (AE) models are the foremost broadly utilized models, taken after by Convolutional Neural Systems (CNNs) and Repetitive Neural Systems (RNNs). The MovieLens and Amazon audit datasets are the foremost habitually utilized for assessment, with motion picture and e-commerce spaces being the foremost common applications. Exactness and Root Cruel Squared Blunder (RMSE) are the prevailing measurements for evaluating RS execution, advertising a comprehensive see of current patterns and challenges in profound learning for RS.

Aminu Dau and Naomie Salim from the Staff of Designing, School of Computing, Universiti Teknologi Malaysia, Johor Bahru, Malaysia, along side Aminu Dau from Hassan Usman Katsina Polytechnic, Katsina, Katsina State, Nigeria, show a efficient writing audit (SLR) on profound learning-based recommender frameworks (RS). These frameworks address the data over-burden issue in zones like e-commerce, amusement, and social media. In spite of the victory of classical RS strategies, challenges like cold begin and information sparsity endure. Profound learning, especially in applications such as Normal Dialect Preparing (NLP) and picture preparing, has appeared guarantee in making strides RS execution. This paper surveys existing profound learning-based RS ponders to supply bits of knowledge into current patterns and challenges. Through the SLR strategy, it identifies autoencoder (AE) models as the foremost broadly utilized profound learning architecture, taken after by Convolutional Neural Systems (CNNs) and Repetitive Neural Systems (RNNs). The MovieLens and Amazon audit datasets are the foremost prevalent for assessment, and precision and Root Cruel Squared Mistake (RMSE) are the foremost common execution metrics.

Liping Liu in their work "e-Commerce Personalized Proposal Based on Machine Learning Innovation" (2022) looks at the challenges of data over-burden in e-commerce and investigates

how personalized suggestion frameworks fueled by machine learning can address this issue. The paper gives an in-depth examination of different e-commerce suggestion advances and calculations, proposing an progressed design that meets the precision and real-time prerequisites of present day e-commerce stages. The framework is partitioned into two fundamental components: offline mining and online recommendation, with each parts capacities and advances discussed. The paper compares user-based, collaborative sifting, and content-based recommender frameworks, highlighting their respective qualities and confinements. It too distinguishes common issues in existing frameworks, such as a need of personalized proposals, decreased pertinence, and destitute convenience. To address these challenges, the creator plans a cross breed suggestion framework combining three calculations and conducts tests to assess its execution. The comes about recommend that variables like client wage, shopping encounter, item costs, quality, suggestion significance, credit assessment, and benefit quality emphatically affect client obtaining readiness and behavior. The paper concludes with experiences into how e-commerce [7] stages can improve personalized suggestion services[4] by consolidating these impacting variables.

3. PROPOSED SYSTEM

A cross breed machine learning algorithm[6] in which Collaborative Sifting suggests clothing things based on the inclinations of comparable clients, either by analyzing client behavior (user-based) or distinguishing things that are habitually enjoyed together (item-based). Content-Based Filtering[10] recommends outfits based on their highlights, such as color, fashion, and texture, coordinating them to a user's past choices. k-Nearest Neighbors (k-NN) is utilized in both strategies to discover comparative clients or things by calculating closeness with the assistance of tensorflow. By combining these approaches, the framework can offer personalized and different mold recommendations [3], progressing the shopping involvement and tending to challenges like cold-start issues and constrained thing disclosure.

A. User-Based Collaborative Filtering:

Recommends things to a client based on what comparative clients have preferred. It recognizes clients with comparable tastes by comparing their intuitive (e.g., appraisals, buys) with different items.

Example: In the event that Client A and Client B both enjoyed a set of clothing things, and Client A likes a modern dress, the framework will suggest this dress to Client B.

B. Item-Based Collaborative Filtering:

Recommends things comparative to what a user has enjoyed within the past. It recognizes things that are commonly enjoyed together by different users[11].

Example: On the off chance that numerous clients who bought a particular combine of pants moreover bought a certain sort of t-shirt, at that point the framework would prescribe this t-shirt to clients who have appeared intrigued in those jeans.

C. k-Nearest Neighbors (k-NN) in Proposal Systems

k-Nearest Neighbors (k-NN) could be a machine learning calculation that can be utilized in both collaborative sifting and content-based sifting. It works by finding the "k" most comparative things (or clients) based on a separate or likeness measure.

How It Works in Collaborative Filtering:

User-Based k-NN: For a given client, discover "k" closest neighbors (other clients) who have comparative tastes and prescribe things that these neighbors have enjoyed but the target client hasn't associating with.

Item-Based k-NN: For a given thing, discover "k" comparable things (based on client intelligent or traits), and suggest those to clients who have associating with the first item.

How It Works in Content-Based Filtering:

Item-Based k-NN: Given an thing, k-NN finds other things with comparative properties (e.g., same class in a motion picture suggestion framework, or comparative fashion in a clothing store) and suggests those things to the client [8].

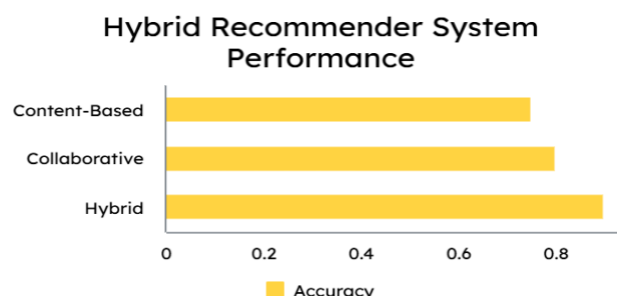


Fig -1: comparison

4.WORK FLOW OF THE PROPOSED SYSTEM

The client submits their points of interest through the input frame. The backend forms this information, approves it, and calls the AI demonstrate for clothing suggestions. The backend stores the information and suggestions, at that point returns them to the frontend for display. At last, the client can associate with the suggestions and investigate more options.

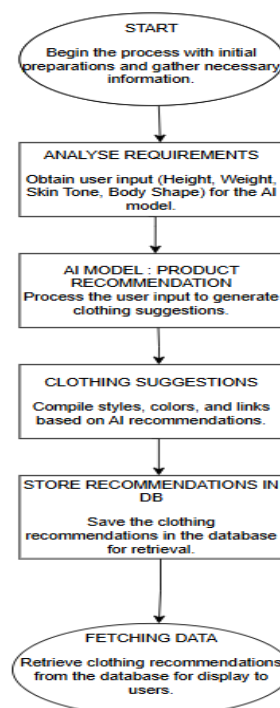


Fig -2: Workflow

From Fig2 we get the diagram of the method of how a client interact with a individual beautician site, beginning from their visit to the domestic page. After clicking the "Get Begun" button, the client is diverted to a frame where they yield their individual points of interest (stature, weight, skin tone, and body shape). The submitted information is sent to the Jar backend , which forms the data by to begin with approving the input. On the off chance that the information is substantial, the backend calls an AI demonstrate to create personalized clothing suggestions, which are at that point put away within the database at the side the data. The framework returns these suggestions and shows them on the proposals page. The client can connect with the recommendations, investigating diverse clothing choices, and can select to return to the domestic page or get to the Contact/About pages for more data. This workflow guarantees that the client gets custom fitted mold exhortation whereas keeping up consistent communication between the frontend (client interface), backend , and the AI proposal model.

5. DESIGN AND IMPLEMENTATION

A. Landing page

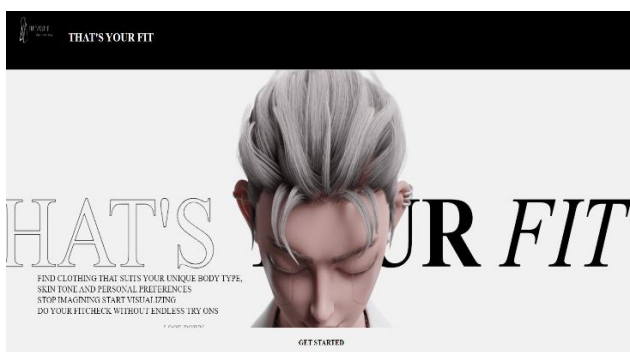


Fig -3: Landing page

From figure 3 the landing page presents an engaging, fashion-focused concept designed for a personalized online wardrobe experience emphasizing a personalized approach to finding clothing that matches the user's unique style and personality which includes a stylized 3D avatar, adding a modern, interactive feel and suggesting a playful and user-centric approach to fashion customization.

B. User input collection

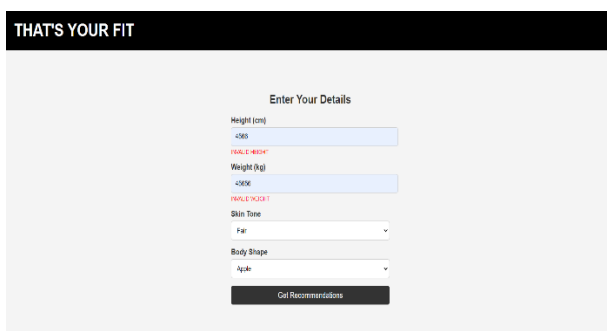


Fig -4: Data collection

From figure 4 This landing page serves as a personalized input form for users to receive fashion recommendations tailored to their unique body metrics and characteristics. It prompts users to "Enter Your Details," including height, weight, skin tone, and body shape, to customize clothing

suggestions. Once the required information is filled in, users can click the "Get Recommendations" button to receive curated style options suited to their physique and appearance, enhancing their shopping experience with a personal touch. The clean, minimalistic design keeps the focus on the input form, making it easy for users to navigate and engage with the service.

C. Recommendation page

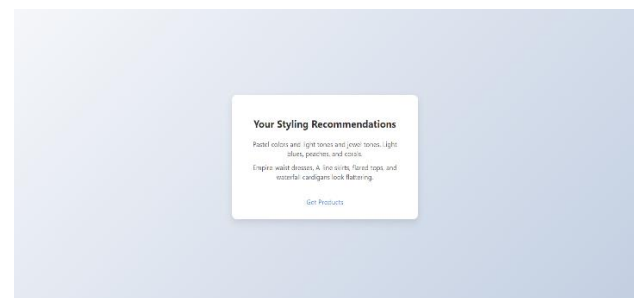


Fig -5: recommendation

From figure 5 The page provides personalized styling recommendations based on user input, enhancing the shopping experience with tailored fashion advice. The main section, titled "Your Styling Recommendations," offers specific fashion tips, suggesting suitable colors (like pastel and light tones) and styles (such as empire-waist dresses, flared tops, and boot-cut pants) that would complement the user's features. A "Get Fit Ideas" button invites users to explore these curated suggestions further, while an optional filter on the right allows users to refine selections based on price. This setup aims to create a smooth, guided shopping journey by focusing on styles that best flatter each individual.

D. products page

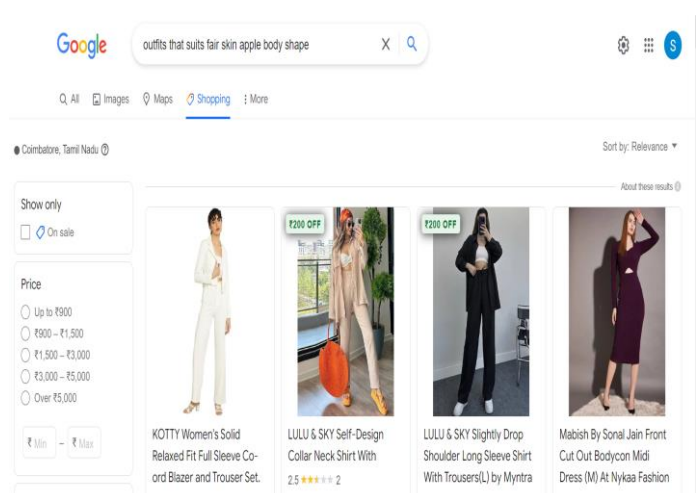


Fig -6: products

Fig 6 appears with a message encouraging the user to get fashion recommendations related to body shape. This page shows search results for outfits that suit for a particular user's input. The results display images of various clothing items from different fashion retailers.

E. 3D model



Fig -7: model

In figure 7 a 3D model is created to do virtual try ons of the selected product.

6.RESULT ANALYSIS

The personalized clothing proposal framework illustrated promising comes about in giving custom-made furnish proposals based on client properties. The generative AI demonstrate effectively produced reasonable clothing pictures that adjusted with client inclinations and body characteristics. The system's integration with the MongoDB database guaranteed secure information administration and productive recovery of client information.

However, encourage refinements are required to progress suggestion exactness and client fulfillment. Regions for future inquire about incorporate investigating progressed generative models, incorporating real-time design patterns, and refining the suggestion calculation to consider different client inclinations. Furthermore, growing the dataset to incorporate a wider extend of clothing styles and client socioeconomics will improve the system's capacity to supply really personalized recommendations.

7. CONCLUSION AND FUTURE WORK

This report has illustrated the potential of leveraging AI-driven models to improve client involvement by giving custom fitted mold recommendations. The integration of an AI show with a vigorous dataset, combined with a user-friendly interface, permits clients to get personalized clothing proposals based on their body shape, stature, weight, and skin tone. The utilize of an SQLite database has encouraged proficient information administration and recovery, contributing to a smooth and responsive encounter for conclusion clients. Generally, the paper exhibits the capability of mixing AI with web advancement to form a keen and intuitively individual styling solution.

To advance upgrade and refine this paper, a few enhancements are proposed. These incorporate improved dataset integration to extend the differences and exactness of suggestions, and optimization of the machine learning demonstrate for superior execution and effectiveness. Growing client profiles and inclinations will permit for a more personalized involvement,

whereas executing real-time proposal upgrades will guarantee clients get the most recent recommendations.

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