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AI Driven Fashion Trend Prediction

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Abstract:
Fashion manufacturers and brands are unaware of what customers desire because they still depend on old school manual methods. This challenge becomes more acute with Generation Z, who are demanding one-of-a-kind and environmentally-friendly shopping experiences. Using machine learning to improve the preciseness of the categorical results of fashion trends can be the solution for the problems discussed above. It predicts precisely, relying on past sale data, social media trends, and extra components to stay ahead of the businesses. It can process data in real-time, allowing it to continuously learn and adapt, ultimately making insights that are relevant to fast changing consumer behaviour.
In a way, AI powered fashion trend prediction, target Random Forest based model for predicting fashion trends using historical data and providing robust interpretations of the predictions. We use an advanced generative AI image synthesis tool known as Stable Diffusion to generate high quality images that portray the aesthetic corresponding to predict emerging styles. By combining these two technologies, designers, manufacturers, and businesses can make intelligent and informed decisions by anticipating and visualizing future fashion trends.
Keywords: AI, Machine Learning, Random Forest, XGBoost.

1.INTRODUCTION

Fashion is an ever-evolving industry influenced by cultural shifts, social media, celebrity endorsements, and consumer behavior. Predicting upcoming trends has traditionally relied on manual analysis, historical sales data, and expert intuition. However, these conventional methods often fail to keep pace with the rapid changes in fashion, particularly among Generation Z consumers who prioritize individuality, digital trends, and sustainability. The demand for accurate, data-driven fashion forecasting has never been higher, prompting the industry to explore advanced technological solutions.
Machine learning (ML) and artificial intelligence (AI) have proved to be powerful tools used to analyze extensive datasets and uncover latent patterns in consumer preferences. AI alternatives enable the processing of vast amounts of real-time data from e-commerce platforms, social media and runway shows, unlike traditional forecasting methods. This enables businesses to more accurately forecast new trends and make informed decisions about product design, marketing strategy, and ad inventory management.
The emphasis of this study lies on the implementation of Random Forest models for predictive trend analysis and Stable Diffusion for AI-generated fashion visuals. AI Driven fashion Trend Prediction allows brands and designers to identify future trends, improve customer interaction, and minimize the risk of unsold products. Furthermore, AI-powered forecasting promotes sustainable fashion practices, reducing overproduction and waste, an area increasingly important as the fashion industry shifts toward environmental responsibility.
AI for trend prediction enables the fashion industry to move from reactive decision-making toward a proactive, data-informed future. This research explores the methodologies and impact of AI-powered fashion forecasting, highlighting its potential to revolutionize the industry by ensuring brands remain competitive in a fast-changing market.

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2.LITERATURE REVIEW

2.1 Introduction

We are making switch over different conventional paradigms using Fashion analytics and artificial intelligence. Recent developments of advanced modular computation, specifically machine learning based sales demand forecasting systems, has granted exceptional insight to trends in the market place, providing directionality on fluctuations in demand and buyer behavior. A major breakthrough in the AI design field includes the AI-generated designs concluding the creative process using deep learning architectures like Generative Adversarial Networks (GANs) and Variation Auto encoders (VAEs) for data-driven designs inspiration.

Women's denim wear especially pants and jeans constitute an important part of the world fashion market. With the speed at which consumer tastes change, sustainability, and economic fluctuations, there is a need for solid forecasting models which do not merely project sales trends but are also helpful in automated designing. This review of literature aims to focus research activities in three main directions: analytics for fashion sales, design automation in fashion, and women's consumer behavior in jeans and pants. The review reveals and explains gaps that are found within the limited scope of combining sales forecast predictive analytics with AI-assisted fashion generation.

2.2 Review of Existing Studies

A. Sales Prediction in the Fashion Industry

With the introduction of machine learning and deep learning models, fashion sales forecasting has transformed dramatically. Time-series forecasting has certainly made use of the traditional techniques like Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA). However, these statistical methods have been outperformed by the sophisticated world of fashion because they fail to capture the non-linear and dynamic aspects of the industry. To tackle this issue, deep learning methods like Long Short-Term Memory (LSTM) networks and Bidirectional LSTMs have been developed, proving to have much better predictive accuracy in datasets that are highly variable.

The further expansion includes the use of Random Forest Regressors and Gradient Boosting Machines (GBMs). These new methods are successful in recognizing sales patterns based on previous purchases, seasonality, and other external economic factors. Additionally, sales forecasting in e-commerce is taken a notch higher by combining Convolutional Neural Networks (CNNs) with LSTMs to use visual and textual metadata.

One important work looked into transaction records of Amazon Fashion, proving that deep convolutional models combined with LSTM-based encoders perform much better than the previously established forecasting methods. Despite these findings, much of the research still

B. AI in Fashion Design

AI as a concept became widely adopted for fashion design, with Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) being employed to generate designs based on past trends and consumer behavior. AI has exhibited competencies to generate fashion designs over time by conducting research centred around Style GAN and P-GANs (Progressively Growing GANs) to create new designs, mirroring changing aesthetic tastes and seeking to adapt them accordingly. Impressive work used Gaussian Mixture Models (GMMs) paired with GANs for coherent and stylistically-appropriate fashion designs. It utilizes latent space representations from the generator to create groups of similar aesthetic items and to produce compliments of AI aided collections.

Moreover, AI-driven design tools have already powered platforms like Myntra, Zalando, and ASOS, where a neural network assesses consumer interaction data to provide suggestions for AI-curated apparel. Nevertheless, research on AI-generated fashion designs on women’s denim wear in particular is sparse. AI-generated design has not been empirically validated to have an effect on real sales performance, warranting this as an area for future investigation. In-depth analysis of how these AI-generated innovations not only facilitate convenience, but also when combined with

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future intelligent customer engagement platforms impact actual purchasing behaviour and overall sales performance could significantly aid development of future AI-based fashion analytics.

C. Consumer Trends in Women's Jeans & Pants

Consumer interest for women's denim and pants are continually evolving, steered by a wide range of factors, such as the influence of social media, awareness of sustainability and macroeconomic conditions. Recent market analysis suggests a come down in demand for skinny jeans, replaced by a growing popularity in wide-leg, cargo and jogger styles. One more important trend fueling consumer demand is sustainability. According to a report (2022) by McKinsey & Company, more than 74% of Generation Z consumers prefer denim jeans from sustainable materials and tend to buy from brands that prioritise ethical sourcing and transparency.

A large-scale fashion dataset derived from Instagram, Pinterest, and e-commerce reviews has shown that consumer engagement with loose-fitting and comfort-driven denim has surged post-pandemic. Furthermore, studies have identified fabric innovation as a key determinant of purchasing behaviour, with increased preference for organic cotton, recycled denim, and stretch-infused blends.

2.3 Comparative Studies & Research Gap

Existing methodologies in fashion research have been analysed and it is revealed that the industry adopts a silo mentality, with sales forecasting and AI-driven design being treated as separate disciplines. There has been considerable research in the area of fashion forecasting using machine learning models and a separate body of work on GAN-based AI fashion design but very few studies have attempted to converge both of these.

For example:

-The existing literature on fashion sales prediction emphasizes demand forecasting as a function of historical sales patterns and seasonal effects, with no studies explicitly integrating AI-computed visuals into predictive models.

- In contrast, the AI-driven research on fashion design has discussed and experimented with the aesthetic and creative aspects without conducting empirical validation on it improving sales.

- Previous studies have accentuated changing consumer behaviour in women's denim trends, but do not explore predictive analytics in conjunction with AI-generated denim design.

This research attempts to fill this gap through combination of AI-based design synthesis and predictive analytics to provide fashion retailers with holistic decision support tool. Combined with sales forecasting models, AI-generated women's jeans and pants can help give manufacturers, retailers, and designers insights about the line of jeans or pants they can prepare for sale.

To conclude, this review of literature describes the need to understand the impact of AI within the fashion industry, specifically on predictive sales modeling and automatic fashion design. There has been a lot of progress with the application of Generative AI in Fashion (product design) as well as with machine learning for sales forecasting. However, not much work has been done on the integration of these for the empowerment of Generation Z and other numerous cohorts in their buying decisions.

Some key findings from this review include:

- AI fashion design dongles could change the landscape of fashion; however, they require additional support in the form of experimental acceptance from the consumers and the market.

- Sales forecasting based on machine learning is predictive in nature, but lacks the AI design trend generation.

-With the adoption of AI technology, consumer shopping habits that pertain to denim jeans is adjusting and changing. This shift now needs tracking and predicting.

To fill the gaps, this study intends to propose a comprehensive model where an AI's predictive design capabilities can directly aid in predictive analytics, resulting in prescriptive insights that are helpful for designers and manufacturers as well as retail. It will assist moving towards a more AI-powered fashion forecasting where a greater balance between what consumers want and what products get developed is achieved

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3. RESEARCH METHODS

The Random Forest algorithm plays a key role in forecasting monthly sales of fashion items, which helps calculate the trend score. This model learns from past data spotting patterns in features like month, type, color, fit, and others to predict sales. Once trained, it can handle new data about a fresh fashion piece by first preparing it (such as turning word-based features into numbers) and then estimating its monthly sales. This sales estimate combines with the expected rating (from the XGBoost model) through a special formula to produce the trend score. This score (1) potential success of a product by balancing how well it sells with how satisfied custon on their ratings. It employs a method known as Random Forest, which constructs numerous decision trees and averages their predictions to achieve accurate and dependable sales forecasts. This approach enhances the system's ability to predict future fashion trends effectively.

$$\hat{y}RF = \frac{1}{B}\sum_{b=1}^{B} \hat{y}b(x)$$

Where:

- $\hat{y}b(x)$: Prediction of the b-th tree for input x
- B: Total number of trees in the forest

XGBoost has an impact on predicting fashion product ratings. This algorithm shines when it comes to structured data and regression tasks. XGBoost builds up its model by adding decision trees one after another. Each new tree fixes mistakes from the ones before it. It aims to strike a balance between accuracy and efficiency. XGBoost handles missing data, performs well on large datasets, and produces reliable outcomes by merging forecasts from numerous trees. In this case, XGBoost studies historical information to identify patterns in features such as Month, type, color, and fit.

Then it guesses the rating for new fashion items. This rating guess teams up with sales predictions (from Random Forest) to figure out a trend score. This score gives a full picture of how well a product might do, looking at both how happy customers are (ratings) and how well it sells.

Objective Function:

$$Obj(\theta) = \sum_{i=1}^{n} L(y_i, \hat{y}_i) + \sum_{k=1}^{k} \Omega(f_k) \quad (2)$$

Where:

- $L(y_i, \hat{y}_i)$: Loss function (e.g., mean squared error for regression)
- $\Omega(f_k)$: Regularization term for the k-th tree.

Additive Model:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \quad (3)$$

Where:

- $\hat{y}_i^{(t)}$: Prediction of the i-th instance at step t.
- $f_t(x_i)$: Output of the new tree at step t.

Gradient and Hessian

$$g_i = \frac{\partial L(y_i, \hat{y}i)}{\partial \hat{y}_i} = \hat{y}_i - y_i \quad (4)$$

$$h_i = \frac{\partial^2 L(y_i, \hat{y}_i)}{\partial \hat{y}_i^2} = 1 \quad (5)$$

Where:

- g_i: Gradient of the loss function for instance i.
- h_i: Hessian of the loss function for instance i.

Trend Score

$$\text{trend}_{\text{score}} = \left(\frac{\text{predicted\_sales}}{\text{max\_sales}} \times \text{sales\_weight} + \frac{\text{predicted\_rating}}{\text{max\_rating}} \times \text{rating\_weight}\right) \times 100$$

Where:

- predicted_sales: Predicted sales value from random forest model.
- predicted_rating: Predicted rating value from XGBoost model.

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- max_sales: Maximum sales value in the dataset (used for normalization)
- max_rating: Maximum rating (default is 5)
- sales_weight: Weight given to sales in the trend score (default is 0.7)
- rating_weight: Weight given to ratings in the trend score (default is 0.3)

3.1 Stable Diffusion: Image Generation and Image Fusion

The technology of Stable Diffusion is utilized in two ways in the production of women's jeans and pants; creating new designs and infusing different features from various pictures into those designs. It has a critical role in creating new designs by gaining insight from its past trend and incorporating elements from targeted images.

A. Image Generation

The power of the deep-learning model Stable Diffusion, for example, is that it thrives on descriptions. So it was used to make new fashions thrown up from an existing dataset about jeans and pants designs. Designers can input certain attributes such as material and fit, preference for styles or cuts, or any other requirements. Then the programme will output new synthesized pictures that match what you've given it. This allows for exploration of innovative and trendy designs, without needing to draw by hand or prototype.

B. Image fusion

There are also important applications in image merging in stable spread. The technique is to merge the properties of many selected images to create a new design idea. Similarly, the designer in our approach chooses two former jeans or pants design, and the model blends their properties in the silhouette, ornamentation and cutter-like symptoms, textures and cut-to-to-to-an unique hybrid creates design. Consequently, new designs should be stored by elements from the previous styles that are well -liked or they will not be popular. And also that an avant -garde will be done in style.

By incorporating stable spread into the workflow, our project improves creativity and efficiency so that designers can quickly generate and change fashion images. This AI-operated approach not only streamlines the design process, but also helps manufacturers to make data-driven decisions by coordinating new styles with estimated sales trends.

3.2 Process Flow

A. Designer

In the AI's prediction system, the designer flood shows the sequential workflow to a fashion designer. This systematic approach determines that a fashion designer can generate new designs effectively, which is achieved from both previous fashion images and intuition of technology for their peers.

1. Year Selection

- User starts the Process by choosing a certain year or is era for Trend Analysis.
- This enables user to find out past trends that can re-emerge with contemporary modification.

2. Selecting Two Images

- Two fashion images, either from past collections or suggested by an AI, are chosen by the designer.
- These images act as the foundation for the new design idea.

3. Generating New Images from Selected Attributes

- AI-based models analyze the selected images and pullout features such as fabric texture, color combinations, and silhouettes.
- By using those extracted features and considering anticipated future trends, a new design is created.

4. Graph Analysis of Each Image

- They employ graphical methods of trend analysis to study the generated designs.

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• This stage allows the evaluation of which aspects of the design are likely to capture attention through social media engagement and historical sales.

5. Designer Sending Newly Generated Image to Manufacturer

• After the best design is chosen, the designer completes the picture and sends it to the manufacturer for making models and mass production.

6. End of the Process

• At this stage, the role of the designer is completed and the manufacturer takes over for further production and market distribution.

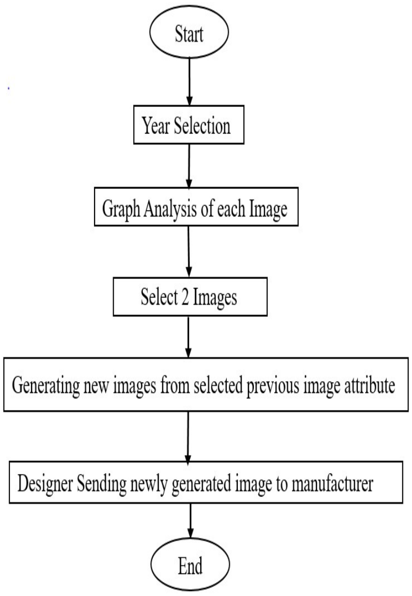

FIGURE 3.1: Designer Process Flow

B. Manufacturer

Manufacturer Flowchart explains how manufacturers validate and further the AI team design and score analyze predictions. This guarantees that only the most promising fashion trends are selected for production while managing resources and cutting down on unwarranted expenditure.

1. Start of Process

• The designer inputs the desired design requirements and the AI works on generating a final product. The manufacturer receives the AI generated design.

• This triggers the start of the evaluation process for the production.

2. Analyse Predicted Trend Score

• The AI models have already generated a trend score which the manufacturer checks to gauge the popularity of the design.

• The higher the score, the lesser the chances of rejection.

3. Analysis of Generated Images and Graphs

• Further checks are done on the feasibility of the AI generated images in regard to material, production cost, and scalability.

• Trend comparison using graphic elements is done between the new and other successful designs.

4. Decision-Making Process

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- The manufacturer moves on to selection of materials and sample production if they have a positive score result and favorable analysis.
- The designer may be recommended changes if the target parameters aren't met by the design.

5. End of Process

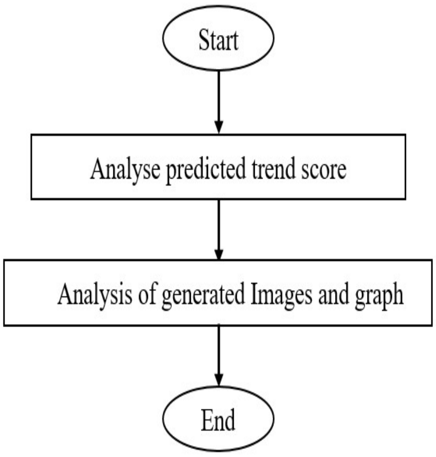

FIGURE 3.2: Manufacturer Process Flow

- The selected designs that are in the later part of the sequence head to mass production while making sure the designs are for predicted upcoming trends and not for something that has already come into the market.

4. RESULT AND DISCUSSION

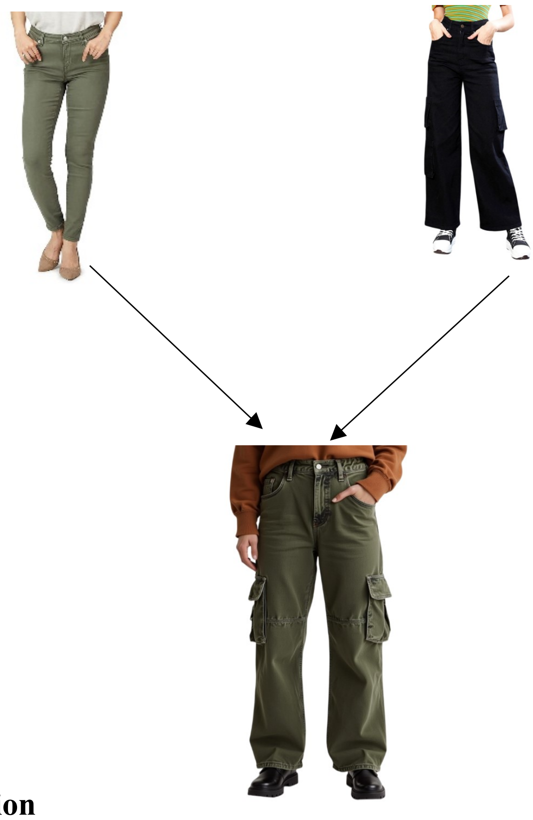

FIGURE **4.1: Image Generation**

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Stable Diffusion is a generative AI model that creates new images by understanding patterns from existing data. It handles by slowly refining a noisy latent representation into a logical image. When generating a new image based on two reference images.
The first step affect analyzing both input images to extract key attributes such as silhouette, color, fabric texture, and structural elements (e.g., pockets, fitting style, and seams).
This feature extraction is performed using models like CLIP (Contrastive Language–Image Pretraining) or Vision Transformers, which encode images into high-dimensional latent representations. Each image is converted into a latent representation, a compressed form where key characteristics are preserved. A controlled interpolation (mixing) is performed in the latent space to combine attributes from both input images. By adjusting weights in the interpolation, one can control how much influence each input image has on the final output. The newly combined latent rendering is used as input for Stable Diffusion. Through a process of resampling, the model continuously refines a noisy image to generate a visually logical result that detain attributes from both input images. This ensures that the output is neither an exact copy of either input but a unique synthesis that balances both styles. Stable Diffusion applies continuous noise removal to increase details and generate a high-quality final image. The generated image retains essential attributes from both reference images while maintaining natural realism and coherence.

This method allows hinder the generation of hybrid fashion design, where the structure of a garment can be linked to the texture, fit or color of another. By using the latent space surgery of stable spread, new fashion concepts can be created effectively, which helps with trend prognosis and virtual prototypes.

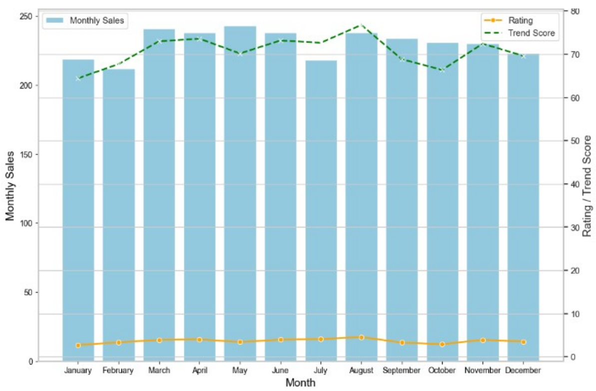

FIGURE 4.2 Graph of Predicted Trend Score of generated Image

The trend result is calculated by historical sales data and customer reviews, which emphasizes each factor based on their impact on demand. The sales trend helps to identify ups and downs in seasonal demand, while customer assessments reflect the possibility of consumer satisfaction and repeated purchase. Using statistical modeling and machine learning techniques is a forecast model trained on previous fashion trends to predict the trend score for next year. The resulting trend score is then thought of using food plotelibs and seborns, where a time series plot refers to the necessary adjustments within months. The trend graph indicates a period of high demand from peaks, helps with storage planning and marketing strategies. This approach provides valuable insight into how the fashion elements generated in the competing market can perform

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5.COMPARATIVE STUDY BASED ON FASHION ATTRIBUTE OF JEANS

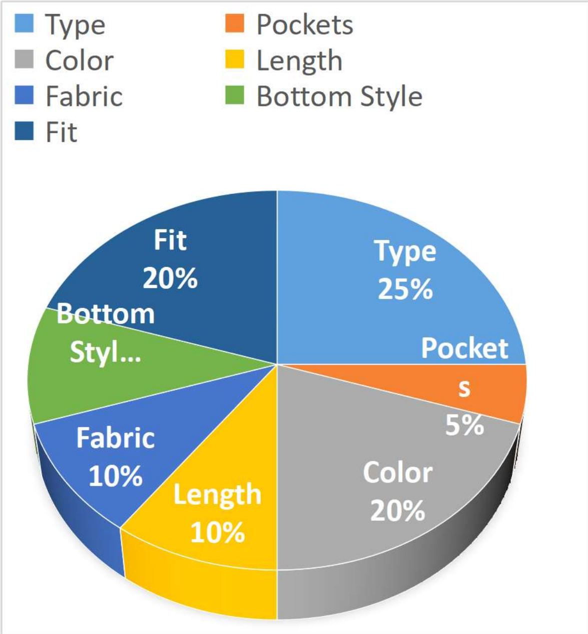

FIGURE 5.1: **Pie chart of Attribute Weightage**

Fashion image is distributed based on its impact on the distinctive weight design and the trend extraction in the fashion image generation. The type (25%) has the highest weight, and determines whether the element generated is a dress, top or down or not. Fit (20%) and color (20%) affect the overall shape, silhouette and visual appeal significantly. Length (10%), substance (10%) and under style (10%) contribute to structural and text -related aspects, ensuring difference in exits. Pocket (5%) plays a smaller yet important role. This weighted approach optimizes AI-related fashion images, ensuring realism and adaptation to today's trends.

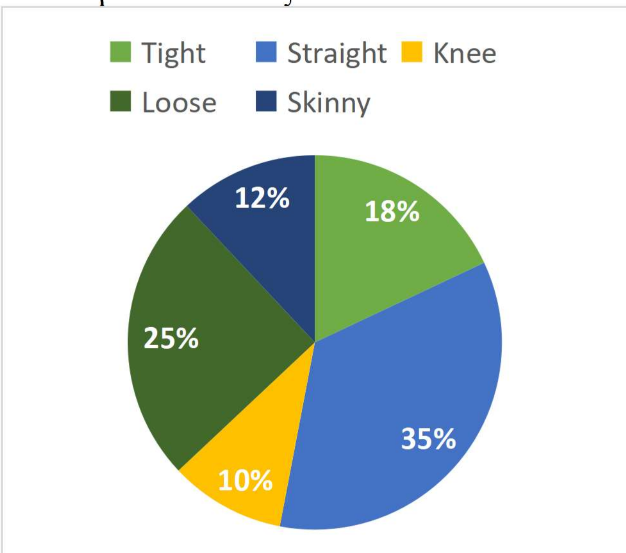

FIGURE **5.2: Pie chart of Type Popularity Trend Data**

Fig 5.2 represents last year's popularity of various jeans styles based on data analysis. **High Waist Jeans (20%)** were the most preferred, followed by **Wideleg Jeans (18%)** and **Mom Jeans (15%),** indicating a trend toward comfort and vintage-inspired fashion. **Cargo and Jogger Jeans (12% each)** gained traction, likely due to their practicality and streetwear appeal, while **Girlfriend Jeans (10%)** maintained a steady following. **Pencil Jeans (8%)** had moderate demand, whereas **Formal**

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Jeans (5%) were the least popular. This data reflects a shift in consumer preferences toward relaxed, high-waisted, and wide-leg styles, aligning with evolving fashion trends.

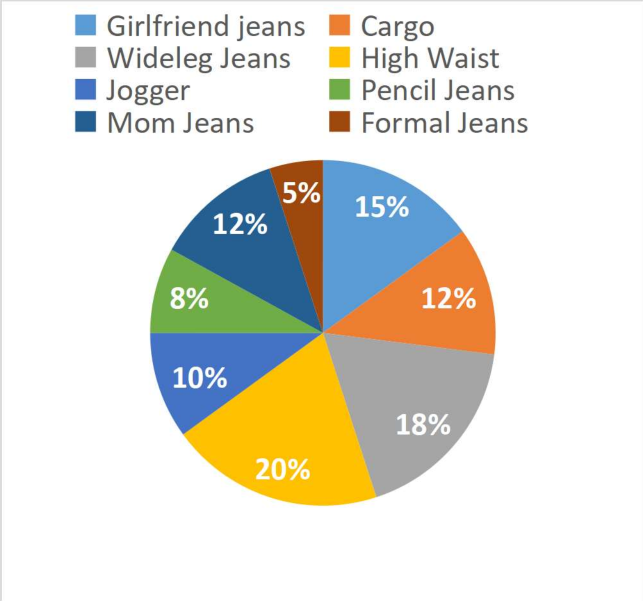

FIGURE **5.3: Pie chart of Fit Popularity Trend Data**

Fig 5.3 illustrates consumer preferences for different jeans fits. **Skinny fit (35%)** remains the most popular choice, reflecting its timeless appeal and versatility. **Loose fit (25%)** follows, highlighting a growing preference for relaxed and comfortable styles. **Tight fit (18%)** maintains a steady demand, catering to those who prefer a snug look. Meanwhile, **Straight fit (12%)** continues to be a classic option, balancing comfort and style. **Knee fit (10%)** is the least popular, suggesting a niche preference. This data indicates a significant trend shift toward comfort-driven and loose-fitting jeans while still valuing the sleek look of skinny jeans.

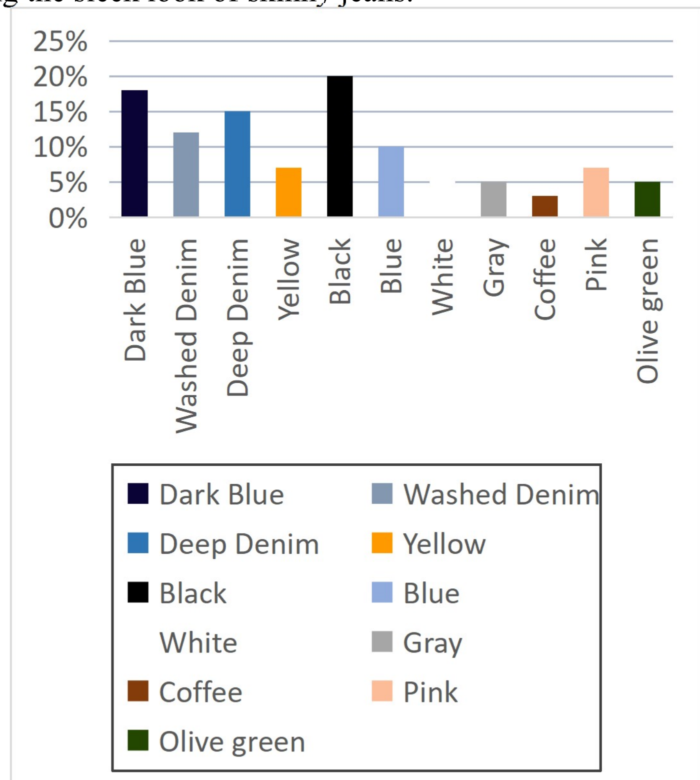

FIGURE **5.4: Bar graph of Color Popularity Score**

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Fig 5.4 presents an analysis of the most preferred jeans colors based on previous data. **Dark blue** stands out as the most popular choice, followed closely by **deep denim** and **washed denim**, reflecting the classic and timeless appeal of blue shades. **Black, white, and blue** maintain moderate popularity, indicating their versatility in styling. **Yellow and pink** show a noticeable preference, suggesting a growing trend toward vibrant hues. Meanwhile, **gray, coffee, and olive green** are the least popular, indicating a niche appeal. The data highlights a strong consumer inclination toward classic blue and neutral shades while hinting at emerging trends in colorful denimchoices.

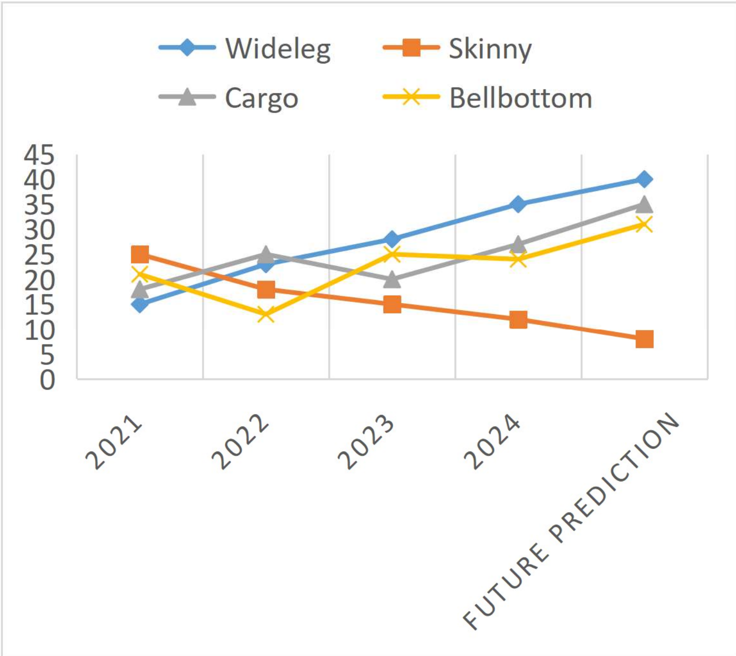

Fig 5.5: Line Graph of Trend Score of Different Types of Jeans

Fig 5.5 illustrates the popularity of four different jean styles **Wide-leg, Skinny, Cargo, and Bellbottom** over the past four years, along with a future trend prediction. **Wide-leg jeans** have shown a consistent rise in popularity and are expected to remain a dominant trend. **Cargo pants** also exhibit an upward trajectory, suggesting increasing consumer interest. **Bellbottoms**, after an initial decline, have regained popularity and are predicted to continue growing. In contrast, **skinny jeans** have been declining in trend score over the years and are expected to lose further appeal in the future. This data highlights a shift toward more relaxed and vintage-inspired styles.

6. LIMITATION AND FUTURE RESEARCH DIRECTIONS

This study does come with some self-imposed limitations. One of the major limitations is the single sourced dataset which could impact the external validity of the study. The dependent sample size could lead to the influence of certain prejudices which would undermine the validity of the models that were designed. It would be useful for future studies to expand their dataset by using other social media platforms along with a more diverse set of consumer interests. Additionally, these other models could serve as a comparison to the current approach and assess which machine learning technique is most appropriate for predicting fashion trends.
So far as the progress made, our research is exclusively focusing on women's jeans and pants. Future research could diversify work scope by including various categories of fashion wearable, including and not limited to shirts, skirts, coats, and even little jewelry to understand the scope of fashion trends better. Further, researchers can design advanced predictive models for outfits based on color and aesthetics to investigate the connection between dressing styles and color choices.

Moreover, hashtag tracking and comment analysis on Instagram, as well as brand tracking could enhance social media analytics to understand broader aspects of shifting consumer preferences, and provide near real-time prediction of new trends. By addressing these limitations and incorporating enhancements in dataset quality and model selection, future research can refine AI-powered fashion predictions, ensuring they remain adaptable, precise, and aligned with evolving market demands.

7. CONCLUSION

This research integrates machine learning and deep learning technologies for predictive analytics, as well as AI-driven fashion design generation for women's pants and jeans. The system uses Random Forest and XGBoost to analyse historical sales data and accurately predict fashion trends. Random Forest identifies important variables and XGBoost enhances the forecasting accuracy by minimizing bias and fine-tuning trend analysis. These forecasting methods enable manufacturers to make market-accurate production and inventory decisions.

In addition, new design concepts are generated using Stable Diffusion by combining salient features from two existing images. Instead of combining images, the model examines and reimagines the clothing design based on selected attributes, for example, fabric type, design fit, and texture. This enables designers to create new innovative styles while retaining some features of previously successful designs, thereby increasing creativity and efficiency in the fashion industry.

To summarize, this paper reveals the efficacy of AI techniques in performing fashion design and trend predictions by automating design processes, easing the workload of data analytics. Follow-up studies could analyse real time customer sentiment data.

8. REFERENCES

1. Ziad Al-Halah, Rainer Stiefelhagen, Kristen Grauman *"Fashion Forward: Forecasting Visual Style in Fashion"* Karlsruhe Institute of Technology, 76131 Karlsruhe, Germany The University of Texas at Austin, 78701 Austin, grauman@cs.utexas.edu
2. Baohua Jin, Bin Lu, Huaiguang Wu, Wenjun Shi,Yan Li *"Fashion Style Forecasts based on Different Price Ranges"* The School of Computer and Communication Engineering, Zhengzhou University of Light Industry, Zhengzhou.
3. FU-HSIEN HUANG , HSIN-MIN LU , (Member, IEEE), AND YAO-WEN HSU *"From Street Photos to Fashion Trends: Leveraging User-Provided Noisy Labels for Fashion Understanding"* Master Program in Statistics, National Taiwan University, Taipei 10617, Taiwan Corresponding author: Hsin-Min Lu (luim@ntu.edu.tw).
4. Imke Grabe Jichen Zhu, Manex Agirrezabal *"Fashion Style Generation: Evolutionary Search with Gaussian Mixture Models in the Latent Space"* IT University of Copenhagen, Copenhagen, Denmark {imgr,jicz} @itu.dk University of Copenhagen, Copenhagen,Denmarkmanex.aguirrezabal@hum.ku.dk.
5. Chunzhi Gu,Haoran Xie , Xuequan Lu (Member, IEEE), Chao Zhang (Member, IEEE) *"CGMVAE: Coupling GMM Prior and GMM Estimator for Unsupervised Clustering and Disentanglement"* Department of Engineering, University of Fukui, Fukui 910-8507, Japan, Japan Advanced Institute of Science and Technology, Nomi 923-1211, Japan3School of Information Technology, Deakin University, Burwood, VIC 3125, Australia Corresponding author: Chao Zhang (zhang@u-fukui.ac.jp).
6. Dwita Adilah, Andry Almsyah "*Model Prediction of the next runway model using decision tree and random forest (Case study: Big Four Fashion Week)*" S1 International ICT Business, School of Economic and Business, Telkom University1 School of Economic and Business, Telkom University.
7. Audrey Aurelia Chang.Cynthia.Devita "*Fashion Trend Forecasting Using Machine Learning Techniques: A Review*" , DOI: 10.1007/978-3-030-90321-3_5 , Nov 2021
8. Nongmeikapar Thoiba Singh; Lakshay Chhikara Prince Raj. Sujal Kumar,"*Fashion Forecasting using Machine Learning Techniques*" DOI: 10.1109/ICICACS57338 202310099844, February 2023, April 2023.

DOI:10.46647/ijetms.2025.v09i02.033 ISSN: 2581-4621

9. Mengyun Shi,Cali Chussid,Pinyi Yang,Menglin Jia ,Van Dyk Lewis ,Wei Cao." *The exploration of artificial intelligence application in fashion trend forecasting.*" Volume 91, Issue 19-20. March 31 2021

10. LaParia Speight,Elena E Karpova University of North Carolina at Greensboro." *Analysis of Fashion Trend Forecasting Industry: Challenges, Opportunities, and Outlooks*" DOI:10.31274/itaa.15872, License CC BY 4.0. December 2022.

11. Wang, T., & Ye, M. (2024). " *TexFit: Text-Driven Fashion Image Editing with Diffusion Models.*" Proceedings of the AAAI Conference on Artificial Intelligence, 38(9), 10198-10206. https://doi.org/10.1609/aaai.v38i9.28885

12. Silhavy, R., Silhavy, P., Prokopova, Z. (eds) Data Science and Intelligent. "*Forecasting Using Machine Learning Techniques: A Review.*" Systems.CoMeSySo 2021. Lecture Notes in Networks and Systems, vol 231. Springer, Cham. 17 November 2021.

13. Nongmeikapam Thoiba Singh,Lakshay Chhikara, Prince Raj,Sujal Kumar "*Fashion Forecasting using Machine LearningTechniques*" DOI: 10.1109/ICICACS57338.2023.10099844

14. Maruf Gogebarkan."*A Novel Approach for Gaussian Mixture Model Clustering Based on Soft Computing Method*"Received November 3, 2021, accepted November 17, 2021, date of publication November 23, 2021,date of current version December 9, 2021. DOI:10.1109/ACCESS.2021.3130066.

15. Pavithra V, Rosy S, Srinishanthini R B, Prinslin L *"Test to image generation usingAI"* DOI:https://doi.org/10.55248/gengpi.234.4.38568
.