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An AI-Driven Decision Support Framework for Ergonomic Optimization in Fashion Manufacturing: Integrating Predictive Analytics and MCDM Techniques

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ABSTRACT

The integration of Artificial Intelligence (AI) with predictive analytics is catalysing digital transformation within the fashion industry, reshaping operational procedures and influencing decision-making practices. This study introduces a decision-making framework that leverages predictive modelling techniques in conjunction with Multi-Criteria Decision-Making (MCDM) methods to enhance ergonomics in fashion manufacturing. The framework recognises the pivotal role of AI in facilitating automated design processes and inventory forecasting, alongside optimising supply chain operations to promote sustainable ergonomic practices. Specifically, the framework employs Autoencoder Recurrent Neural Network (RNN) models—advanced deep learning methods—to deliver improved accuracy in forecasting customer demand and identifying consumer preferences. AI-powered generative design contributes to reduced material waste and enhanced production efficiency, aligning with the goals of operational excellence and ergonomic compliance. Moreover, intelligent logistics systems and Internet of Things (IoT)-driven analytics within supply chain management support cost reduction and risk mitigation efforts. To systematically assess and prioritise ergonomic considerations, the Analytic Hierarchy Process (AHP) technique is incorporated into the framework. This integration facilitates structured evaluations of alternatives, enabling transparent and data-informed decisions that strike a balance between worker comfort, sustainability, and productivity. Additionally, AI applications in fashion retail enhance the consumer experience by enabling virtual product trials, delivering personalised recommendations, and providing interactive digital support. The adoption of AI in fashion retail is largely attributed to its capabilities in simulating product testing and offering tailored customer services, including digital assistance. The proposed framework thus supports sustainable manufacturing practices and worker well-being while fostering robust, data-centric managerial decision-making. Ultimately, the integration of MCDM with predictive analytics and AI forms the foundation for achieving responsible operations and human-centred production design, which are critical for the fashion sector's long-term viability.

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1. Introduction

The integration of AI into the fashion industry brings significant ergonomic advantages for manufacturers, enhancing the efficiency of production engineers and operations teams [20]. The increasing routinisation of tasks within fashion manufacturing exposes workers to various ergonomic risks, including repetitive strain injuries, awkward postures, and inefficient workflows that demand excessive time or skill [6]. AI-driven assistive technologies offer transformative potential by optimising workspace configurations, monitoring worker health, and improving overall production efficiency [3]]. Ergonomic design in manufacturing focuses on tailoring tools, systems, and workspaces to align with human capabilities, thereby ensuring safety, comfort, and productivity [5]. Traditionally, ergonomic assessments in the fashion sector rely on manual evaluations and static workstation configurations [12]. However, such conventional methods fall short in adapting to the dynamic nature of contemporary manufacturing environments. The adoption of AI tools, machine learning algorithms, and real-time monitoring systems introduces AI-generated content (AIGC) into workplaces, enabling continuous tracking and enhancement of performance and safety metrics [32].

AIGC plays a pivotal role in refining ergonomic conditions by generating workplace designs aimed at minimising fatigue and physical strain. AI-powered simulation tools can suggest workstation layouts that mitigate biomechanical stress while promoting optimal posture and movement [23]. For instance, generative AI models may propose improvements to sewing stations, such as adjusting chair heights, altering table inclinations, and eliminating foot pedals. These refinements have been shown to reduce the occurrence of musculoskeletal disorders and facilitate healthier posture during repetitive tasks [26]. Beyond intelligent workstation design, AI-based wearable technologies are being adopted in fashion manufacturing to address ergonomic challenges [14]. These innovations include sensor-equipped gloves, AI-guided posture correction devices, and exoskeletons that detect and rectify improper body movements [2]. Such tools not only deliver real-time feedback but also help prevent chronic injuries, thereby reducing long-term healthcare costs and employee absenteeism [24]. AI-enhanced exoskeletons also assist with material handling by redistributing weight, thereby alleviating pressure on the lower back and joints [21].

Another area where AI contributes significantly to ergonomic improvement is in workflow automation. AI-driven systems utilise real-time production data to identify ergonomic inefficiencies and propose task optimisation strategies [16]. For example, machine learning models analyse workflow distribution, break schedules, and movement patterns to ensure tasks are evenly allocated among workers, thus preventing overburdening and fostering a balanced work environment [30]. Moreover, AI interfaces employing Natural Language Processing (NLP) enable direct communication between employees and ergonomic support systems, delivering immediate feedback and adjustments to work practices [9]. A key component in this evolving framework is the application of MCDM techniques, particularly the AHP. AHP is essential in systematically evaluating and ranking multiple ergonomic factors within the decision-making process. By decomposing complex design challenges into structured hierarchies of goals, criteria, and alternatives, AHP enables transparent, rational, and data-driven selections. For example, when choosing between different workstation designs, AHP considers variables such as biomechanical load, user comfort, cost-efficiency, and adaptability to various body types, ensuring that both ergonomic and operational objectives are addressed.

AI is also revolutionising ergonomic training in manufacturing. Traditional training approaches were often static and lacked the adaptability to meet individual ergonomic needs [4]. In contrast, AI-powered Virtual Reality (VR) and Augmented Reality (AR) simulations provide personalised training modules tailored to each worker's ergonomic challenges. These immersive environments allow employees to practise correct lifting techniques, seating postures, and safe movements virtually before transitioning to actual work scenarios [8]. Furthermore, these AI-driven modules adapt in real time based on user feedback and performance metrics, facilitating more effective and responsive learning [31]. Despite its promise, implementing AIGC-based ergonomic solutions presents several challenges. These include high initial capital investment, the need for specialised infrastructure, and potential resistance from workers adapting to AI-integrated systems [10]. Additionally, ethical concerns around AI-based monitoring and data privacy must be addressed in line with regulatory standards and employee expectations [22]. Nonetheless, advancements in AI, generative modelling, and real-time analytics are steadily reducing costs and improving accessibility, making AIGC-based ergonomic interventions increasingly viable for future applications [28]. The application of AIGC in ergonomic enhancements marks an important advancement towards a more human-centred manufacturing paradigm. These AI-based systems actively anticipate and mitigate ergonomic hazards, contributing to safer, more efficient, and sustainable workplaces. Future developments in predictive analytics, adaptive robotics, and intelligent automation are expected to further improve productivity and employee wellbeing by fostering ergonomically sound manufacturing practices. At present, the emergence of AIGC is redefining industry standards of ergonomic excellence, establishing technology as a vital component in achieving operational efficiency centred around human workers [27].

This research project examines the role of AI in fashion enterprises, with particular focus on its utility in automating product development, forecasting fashion trends, managing inventory, and optimising supplier networks. It specifically analyses how deep learning models, such as Autoencoder-RNN, enhance demand forecasting and consumer preference analysis. The study also investigates the impact of predictive AI analytics on sustainable production practices, operational efficiency, and cost reduction. The findings demonstrate that AI integration is reshaping strategic decision-making in fashion, fostering sustainable business practices while enduring profitability.

2. Literature Review

The application of AI-based ergonomic solutions in fashion manufacturing has been examined with respect to their effectiveness, practicality, and contribution to workplace safety. Various studies have explored the enhancement of worker comfort and productivity through technological advancements such as AI-enabled workstation optimisation, motion tracking, and intelligent assistive devices. Innovations including AI-powered exoskeletons, real-time posture correction systems, and workflow management platforms have demonstrated significant ergonomic benefits. In addition to their technical advantages, the economic and regulatory aspects of adopting these technologies have also been considered. These include cost-benefit analyses, relevant policy frameworks, and alignment with long-term sustainability goals. As the fashion sector progressively shifts towards more worker-centric and efficient production models, this literature review identifies key innovations with the greatest impact, evaluates their associated advantages, and highlights current limitations in the deployment of AIGC-based ergonomic interventions. The most critical methods employed in the implementation of AIGC-driven ergonomic strategies are summarised in the following table, along with their respective strengths and limitations. Table 1 presents the problem formulations associated with traditional ergonomic techniques for comparison.

Table 1
Problem Formulation of the Conventional Techniques

Author(s)	Techniques Involved	Advantages	Disadvantages
Ji et al. [13]	DHM, RULA, Clearance Analysis	Improved Posture, Reduced Strain, Higher Productivity	High Cost, Worker Adaptation Issues
Mousavi and Naeini [17]	AHP in OHS	Better Risk Assessment, Structured Decision-Making	Subjectivity, Reliance on Expert Input
Liu et al. [15]	AHP, Entropy Weight, Cloud Model	Improved Supplier Selection, Balanced Weighting	Data-Intensive, Complex Implementation
Mustajib et al. [18]	AHP-Entropy Grey Clustering	Efficient Sorting, Better Decision Accuracy	Data Pre-Processing, Expert Dependency
Dey and Mondal [7]	REBA for Ergonomic Assessment	Identifies High-Risk Tasks, Posture Improvement	Resistance to Change, Cost Implications

A redeveloped stitching workstation for manual Kolhapuri footwear was proposed using Digital Human Modelling (DHM) to assess ergonomic efficiency through clearance analysis and Rapid Upper Limb Assessment (RULA) [13]. The redesign led to improvements in posture, reduced physical strain, and enhanced productivity. However, the solution involved significant investment and required adaptation from the workforce, and its practical effectiveness needed real-world validation. In the context of occupational health and safety (OHS), a decision-making framework was established using the AHP to rank workplace hazards and assess ergonomic risks [17]. The structured model provided improved clarity in managing complex safety challenges, integrating expert judgement to develop targeted interventions. Although the method enhanced accuracy and transparency, it was limited by subjectivity in pairwise comparisons and dependence on expert consensus, highlighting the need for broader validation and refinement.

An integrated performance assessment model combining AHP, entropy weight method, and cloud modelling was used to evaluate prefabricated component suppliers [15]. AHP facilitated the development of a structured evaluation framework, while the entropy weight method calculated criteria weights objectively based on data variability. The cloud model addressed uncertainty and imprecision in supplier assessment. Although this hybrid model improved decision reliability and supply chain efficiency, the process was resource-intensive, requiring extensive data and expert involvement. A novel multi-criteria sorting technique was introduced by integrating AHP, entropy weighting, and grey clustering to manage uncertainty in remanufacturing core quality [18]. AHP structured the decision process, entropy weighting provided objective prioritisation of criteria, and the grey clustering algorithm enabled sorting of components with ambiguous quality levels. The method enhanced classification accuracy and resource utilisation, though it involved complex implementation and significant data pre-processing, alongside reliance on expert input.

An ergonomic risk assessment was conducted in the apparel finishing sector using the Rapid Entire Body Assessment (REBA) technique, focusing on the impact of body mass index (BMI) on head and neck postures [7]. Through observational analysis of garment workers, high-risk activities such as ironing, quality inspection, and packing were identified. A clear correlation between poor posture and elevated BMI was found, contributing to musculoskeletal strain. Recommendations included redesigning workstations and seats and introducing posture training to enhance safety and performance. While existing ergonomic assessment tools such as DHM, RULA, REBA, AHP, and entropy-based models offer structured evaluation mechanisms, they are constrained by high costs, dependence on expert knowledge, and limited adaptability in dynamic manufacturing contexts. The proposed AIGC-driven approach addresses these limitations by integrating real-time tracking, predictive analytics, and customisable design capabilities. Unlike conventional static models, AIGC systems enable continuous learning and automated ergonomic interventions, resulting in improved safety, efficiency, and scalability across fashion manufacturing environments.

3. Proposed System Model

A comprehensive method is proposed which establishes an AI-based decision support system incorporating MCDM techniques particularly the AHP in combination with predictive analytics to achieve forward-looking ergonomic optimisation in fashion manufacturing. The integration of deep learning models, especially Autoencoder-RNN structures, allows the system to generate accurate demand forecasts and evaluate consumer preferences effectively. These predictive capabilities facilitate automation in design processes and production planning, reducing material wastage and limiting instances of overproduction. The framework further employs generative AI tools to advance sustainable fashion product development while simultaneously improving ergonomic workstation layouts. In parallel, smart logistics systems enhanced by IoT technologies enable real-time tracking and support proactive management of operational risks across the supply chain. Within this structure, AHP serves as a key instrument by systematically organising conflicting ergonomic and operational priorities—such as worker wellbeing, productivity, and sustainability—into a structured hierarchy. By leveraging expert input and pairwise comparisons, the method assigns relative importance to each criterion, promoting a balanced and data-informed decision-making process.

This integrated approach ensures that decision-making throughout the fashion production cycle, from initial design to final distribution, is guided by ethical considerations, operational efficiency, and empirical evidence. The fashion industry is currently undergoing notable transformation. According to projections, global sales within the sector are expected to grow steadily over the next two to three years [28]. Two major shifts have been identified as drivers of this growth: firstly, the emergence of new markets in regions such as Latin America and Asia-Pacific, which are anticipated to account for more than half of global fashion sales; secondly, a decline in reliance on Western markets as the primary source of industry momentum. Technological advances including robotics, augmented and virtual reality, advanced data analytics, mobile connectivity, and artificial intelligence are reshaping the sector. These innovations are influencing not only enterprise strategies but also altering consumer behaviours, with a marked shift toward digital engagement. The conceptual design of the proposed model is illustrated in Figure 1.

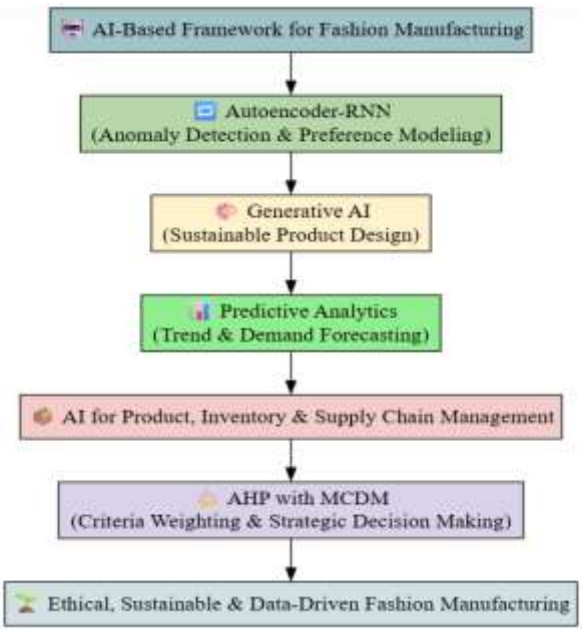

Fig.1: Proposed System Model

The objective of this research is to explore and evaluate the integration of AI automation within the textile and apparel industries. The study investigates various emerging trends across the fashion and textile sectors that are influenced by AI applications. The incorporation of AI has brought about significant transformations in these industries, reshaping traditional practices and operational models. The following section provides an overview of the concept of AI, along with its practical implementation and deployment within the context of textile and apparel manufacturing.

3.1 Autoencoder-RNN

The artificial neural network architecture known as an autoencoder is employed across various applications, including image processing and data denoising. Autoencoders significantly improve anomaly detection accuracy when compared with both linear and kernel Principal Component Analysis (PCA), making them a suitable choice for this study. While linear PCA often fails to detect minor anomalies, autoencoders can identify these with greater precision. Furthermore, the training process for autoencoders is more straightforward, as it avoids the complex mathematical operations associated with kernel PCA. The autoencoder structure consists of three sequential layers. The input layer accepts raw data input, denoted as Xi, which is then encoded and subsequently decoded through hidden layers referred to as the encoder and decoder blocks. The decoder reconstructs encoded features from the final output of the encoder, which compresses the data into a lower-dimensional representation than the original input. The size of the initial input remains equivalent to the resulting output feature vector [33]. To enhance detection capabilities, the study incorporates a RNN model into the autoencoder framework for analysing both consumer and business preferences. This integration addresses the limitations of traditional feedforward neural networks by leveraging the sequential modelling capacity of RNNs. Unlike feedforward networks, RNNs possess recurrent connections that enable them to process sequences, making them well-suited for applications such as speech recognition and language processing [11].

The proposed model processes input data by transforming it into vector representations through a two-step procedure comprising unsupervised pre-training and supervised fine-tuning. During the pre-training phase, features are extracted from the data within an unsupervised framework that compresses the input. Each component of the autoencoder functions as a standard RNN unit. The encoder includes four hidden layers with 64, 32, 16, and 8 channels, respectively. The decoder follows a reversed configuration with layers of 8, 16, 32, and 64 channels. Once the weights and biases are appropriately configured, the RNN-autoencoder learns hierarchical feature representations from unlabelled input data. The final network layer is trained using labelled samples during the supervised fine-tuning stage. To achieve optimal performance, this supervised training criterion must be applied during the refinement process. At the top layer, a SoftMax regression function with two output channels assigns a probability between 0 and 1 to each class label, ensuring that the sum of probabilities equals 1.

3.2 Applications for AI Technique

Fashion is considered one of the world's most valuable industries, with an estimated worth of approximately $3 trillion, representing around 2 percent of the global gross domestic product [19]. For decades, the industry adhered to conventional methods; however, the advent of digital transformation has ushered in notable shifts across its structure and operations. The integration of AI into fashion has been significantly facilitated by digital technologies, which have enhanced access to vast datasets. Retail outlets and online platforms have increasingly adopted AI-powered applications within customer service functions to collect and analyse consumer data, enabling a deeper understanding of individual preferences. Given the constantly evolving nature of fashion trends, AI has proven effective in validating extensive consumer data to forecast emerging styles with greater accuracy. Businesses are also leveraging mobile-enabled virtual assistants and interactive technologies such as smart mirrors, which utilise facial recognition and expression analysis to suggest personalised fashion choices. The application of AI in fashion design has become a widespread practice during the current era of technological advancement.

3.3 Artificial Intelligence for Generating Sustainable Fashion

The fashion industry is widely recognised as a significant contributor to environmental degradation, largely due to its intensive consumption of natural resources, including leather, which often exceed sustainable supply levels. Fast fashion practices involve high volumes of water usage for dyeing processes and lead to considerable textile waste. With new collections introduced monthly and fashion items being replaced weekly, the cycle of consumption exacerbates environmental pressure. In response, the integration of AI into fashion production processes is facilitating a shift towards more sustainable practices. AI supports the development of efficient manufacturing systems aimed at reducing waste, optimising resource utilisation, and ensuring ethical operations throughout the supply chain.

Environmental harm in fashion stems from pollutant emissions during manufacturing, excessive production of textile waste, and escalating carbon footprints. To counter these effects, AI technologies are being employed to design sustainable workflows, introduce intelligent manufacturing mechanisms, and improve supply chain efficiency. A pivotal application in this regard is generative design software, which utilises AI algorithms to create patterns that minimise or eliminate material waste. AI-driven analytical tools enable organisations to better forecast product requirements, thereby reducing surplus production, inventory levels, and associated waste. Moreover, AI contributes to sustainable textile production by supporting fibre selection processes and identifying eco-friendly materials, while also enhancing waste recycling practices.

Furthermore, AI plays a critical role in enabling circular fashion models, particularly by facilitating the sorting and upcycling of used garments. The adoption of AI-powered virtual try-on solutions and intelligent recommendation systems reduces the need for physical samples and product returns, thereby cutting down shipping-related emissions. In addition, blockchain technology enhanced by AI is being used to ensure end-to-end traceability in the materials supply chain, promoting transparency and accountability in ethical sourcing and labour practices. AI is thus driving the fashion industry's transition towards a more environmentally responsible and ethically conscious future, where technological solutions aid in waste reduction, support fair labour standards, and encourage consumer engagement through personalised and sustainable fashion choices [29].

3.4 Predictive Analytics and AI for Trend and Demand Forecasting

Predictive analytics and AI are significantly transforming trend and demand forecasting, particularly within the fashion, retail, and consumer goods sectors. Traditional forecasting methods, which largely depended on intuition supported by historical sales data, often resulted in inefficiencies such as overproduction, underutilised labour, and inventory shortages. In contrast, AI-driven predictive analytics enables the generation of precise, real-time demand forecasts by analysing vast datasets. These technologies can anticipate emerging fashion trends and consumer preferences well in advance, allowing businesses to respond proactively. Machine learning models support data-informed decision-making in pricing, marketing, and inventory management by accounting for dynamic external variables, including seasonality, economic fluctuations, and competitive strategies. These models refine their predictive accuracy over time through continuous learning. Furthermore, AI-based forecasting contributes to the timely production and delivery of goods, enhancing supply chain efficiency, minimising resource wastage, and lowering operational costs. By reducing excess inventory, enhancing customer satisfaction, and enabling tailored offerings, AI strengthens business performance and sustainability. The integration of AI and predictive analytics into demand and trend forecasting enhances a company's capacity to swiftly adapt to evolving market conditions, strengthens data-driven strategic decisions, and ultimately provides a competitive edge in the rapidly changing consumer landscape [1].

3.5 Artificial Intelligence for Product, Inventory and Supply Chain Management

AI is redefining the management of supply chain operations, inventory control, and product lifecycle by enhancing efficiency, reducing operational costs, and minimising the need for human intervention in decision-making. Traditional supply chain systems often encounter issues such as unpredictable demand shifts, supply chain disruptions, and suboptimal inventory practices, which can result in either stock shortages or excessive inventory. AI-based technologies address these limitations by leveraging automation, machine learning algorithms, and real-time data analysis to optimise resource allocation and operational effectiveness. In product management, AI facilitates demand-aligned production by analysing historical sales data, market trends, and consumer preferences. Predictive analytics and sentiment analysis contribute to more accurate product development cycles, reducing the risks associated with new product launches and improving the alignment between offerings and market expectations [25].

AI-powered inventory management systems incorporate computer vision, IoT sensor networks, and predictive modelling to continuously monitor inventory levels and autonomously detect anomalies. These systems streamline restocking processes, reduce holding costs, and enhance accuracy in inventory planning. Machine learning models further refine inventory strategies by analysing sales trends, supplier lead times, and seasonal fluctuations to ensure optimal stock availability without overburdening storage capacity. In logistics, AI technologies improve supply chain coordination by integrating external data sources, such as traffic conditions and weather forecasts, to enhance delivery efficiency. Optimisation algorithms enable more accurate route planning for last-mile delivery, reducing fuel consumption and minimising delays. Additionally, AI contributes to risk management by forecasting potential disruptions through analysis of macroeconomic indicators, supplier reliability, and geopolitical factors, thereby enabling proactive mitigation strategies. The integration of AI into supply chain, inventory, and product management promotes lean operations by enhancing sustainability, cost efficiency, and responsiveness. Using real-time data and automated decision-making processes, organisations can improve agility, reduce operational risks, and deliver superior customer experiences while simultaneously maximising profitability.

3.6 AHP with MCDM

Within fashion manufacturing, the optimisation of ergonomics through the integration of MCDM techniques and AI offers a systematic and objective means of navigating complex decision-making scenarios. The proposed AI-enabled decision support framework incorporates the AHP within the broader MCDM approach to assess and prioritise ergonomic, operational, environmental, and economic parameters linked to sustainable production systems. Initially, predictive analytics—driven by machine learning models and historical performance data—identifies critical ergonomic risks, indicators of worker comfort, and factors influencing productivity. These variables are subsequently structured within the AHP framework, allowing for the allocation of weighted importance to each criterion based on expert input and real-time operational feedback.

The resulting decision matrix from AHP is subjected to further analysis through an MCDM method such as TOPSIS, VIKOR, or PROMETHEE, facilitating the ranking of optimal manufacturing system configurations, equipment layouts, and workforce scheduling strategies. This integrated approach equips stakeholders with a data-grounded, transparent, and defensible basis for ergonomic decision-making, thereby enhancing occupational health and safety, improving employee comfort, and promoting operational efficiency. Embedding ergonomics within a broader AI-driven manufacturing ecosystem ensures that sustainable fashion production remains aligned with human-centred design principles while also addressing technical feasibility and economic sustainability.

4. Performance Evaluation

AI applications within the fashion industry have significantly enhanced operational efficiency, supported sustainability initiatives, and improved responsiveness to market dynamics in real time. Machine learning-driven predictive analytics facilitate more accurate forecasting of fashion trends, thereby reducing errors in production planning and ensuring that product offerings align closely with consumer preferences. In the context of sustainable fashion, AI contributes by promoting the optimal utilisation of textile resources, thus limiting material waste and mitigating environmental damage. Tools powered by AI for material selection support the adoption of biodegradable and recyclable fabrics, which are essential to the development of circular fashion models. The integration of blockchain with AI enhances transparency across the supply chain, particularly in terms of ethical sourcing and responsible labour practices. AI-based optimisation in supply chain management reduces excess inventory, prevents stockouts and overstocking, and lowers associated operational costs. Furthermore, machine learning models for demand forecasting refine inventory management processes by adjusting stock levels according to accurate consumption patterns. In warehousing operations, advanced AI systems enable automation and improve logistics performance by reducing lead times and increasing distribution efficiency.

In design processes, AI empowers fashion creators to accelerate the development of innovative and trend-responsive garments. Enhanced logistics efficiency is achieved through AI-supported route optimisation and improved resource allocation. Moreover, AI-powered customer service tools, such as chatbots, strengthen customer engagement and satisfaction, fostering brand loyalty. In sustainability-driven operations, machine learning technologies contribute to lower emissions and greater energy efficiency during production. Organisations that incorporate AI-driven systems are positioned to gain strategic advantages, making informed decisions through data analytics. Adopting AI fosters organisational agility and economic resilience, securing a competitive edge in the rapidly evolving fashion landscape. The input images, along with data on commercial preferences and customer demands, are illustrated in Figure 2 and the resulting output in Figure 3.

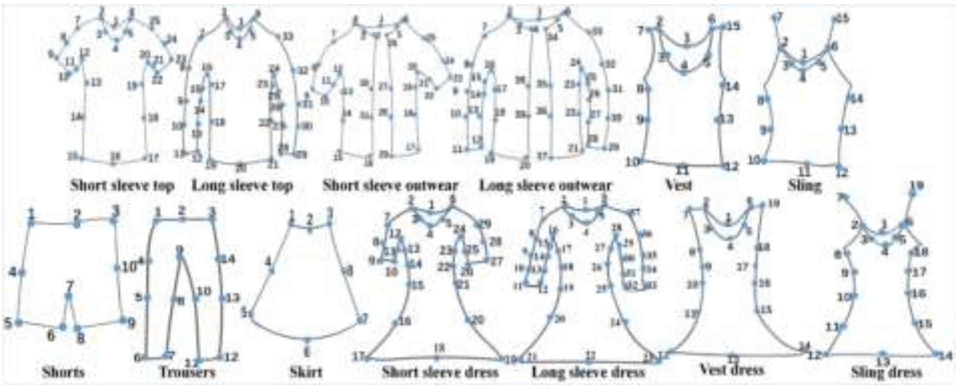

Fig.2: Input Images

Fig.3: Validation of Commercial and Customer Requirements

Figure 4 presents the comparative performance evaluation of multiple AI-based models using standard classification metrics, namely Accuracy, Precision, Recall, and F1-Score. The analysis encompasses four distinct models: the proposed Autoencoder-Recurrent Neural Network (AE-RNN), Faster R-CNN, Mask R-CNN, and Vision Transformer (ViT). Performance values across these metrics range from 65% to 100%, reported as percentages. Among the assessed methods, the AE-RNN model demonstrates superior performance across all four metrics, achieving over 97% in Accuracy, 96% in Precision, approximately 97% in Recall, and 96% in F1-Score. These outcomes confirm AE-RNN as the most effective model within the evaluation framework.

In comparison, the Faster R-CNN model yields the lowest performance, with an Accuracy of 88%, and both Precision and Recall at approximately 85%, resulting in an F1-Score of 86%. Although the Mask R-CNN model shows marginal improvement over Faster R-CNN, attaining around 90% Accuracy, 88% Precision, 89% Recall, and an F1-Score near 88%, its performance remains notably below that of AE-RNN. The ViT model achieves slightly higher metrics than Mask R-CNN, reporting an Accuracy of 91%, Precision of 90.1%, Recall of 91%, and F1-Score of 90.8%. Despite outperforming both R-CNN variants, ViT still does not reach the classification effectiveness demonstrated by AE-RNN. Overall, the AE-RNN model exhibits clear performance dominance, outperforming all other models in each evaluated criterion. This consistent superiority underscores its robustness and reliability for the intended application, as reflected in the substantial differences observed in Accuracy, Precision, Recall, and F1-Score.

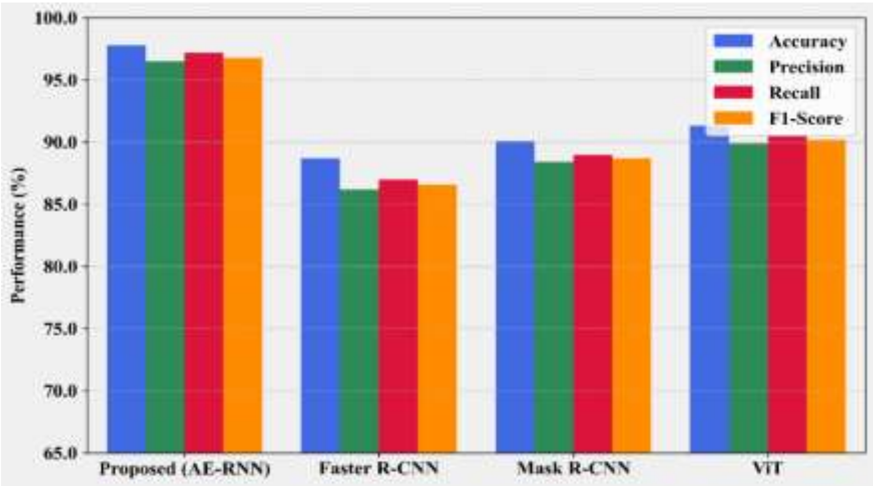

Fig.4: Validation of Accuracy

Figure 5 illustrates a comparative analysis of computational performance metrics for the proposed AE-RNN model alongside Faster R-CNN, Mask R-CNN, and ViT. The evaluation includes three key indicators: inference time (measured in milliseconds and shown in blue), model size (measured in megabytes and represented in green), and floating-point operations (FLOPs, measured in gigaflops and depicted in red). Among the models assessed, AE-RNN demonstrates the highest computational efficiency, combining the lowest inference time with a relatively compact model size of approximately 100 MB and a reduced computational demand of 55 GFLOPs. In contrast, both Faster R-CNN and Mask R-CNN exhibit significantly higher resource consumption, with model sizes averaging around 250 MB, extended inference durations, and elevated FLOPs in the range of 120 to 130 GFLOPs. The ViT model occupies an intermediate position, with a model size of 175 MB and computational complexity of 95 GFLOPs, thereby offering a balance between operational efficiency and predictive performance. Overall, the AE-RNN model proves to be the most computationally efficient of the group, while Faster R-CNN and Mask R-CNN are identified as the most resource-intensive.

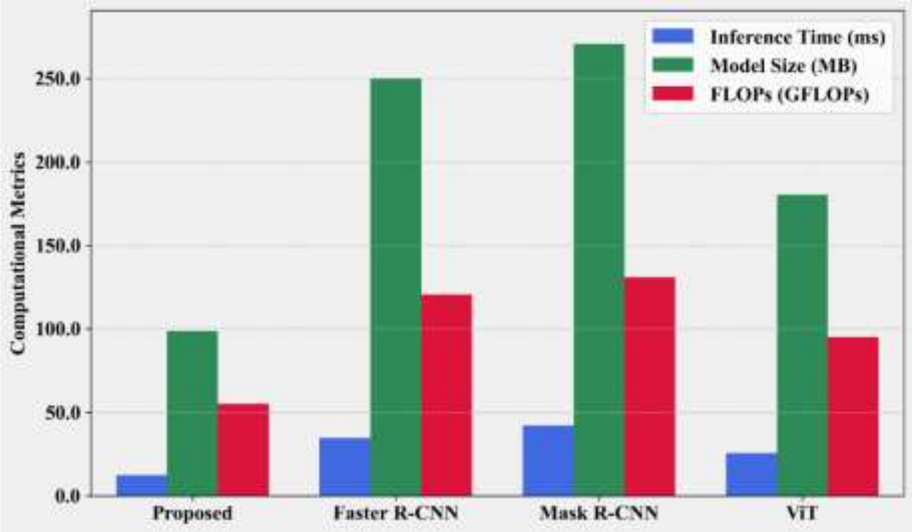

Fig.5: Validation of Computational Metrices

Figure 6 presents a comparative evaluation of the proposed AE-RNN model alongside Faster R-CNN, Mask R-CNN, and ViT, using three key performance metrics: mean Average Precision (mAP) for detection (blue), Intersection over Union (IoU) for segmentation (green), and Top-5 Retrieval accuracy (red). The AE-RNN model demonstrates superior results across all parameters, achieving the highest mAP of approximately 80% and an IoU of nearly 70%, indicating its strong detection and segmentation capabilities. Faster R-CNN and Mask R-CNN exhibit lower detection and segmentation performance, with mAP scores of roughly 75% and 77%, and IoU values around 62% and 64%, respectively. In comparison, the ViT model offers competitive results, attaining a mAP of approximately 78% and an IoU close to 68%. All four models perform consistently well in retrieval tasks, as Top-5 Retrieval accuracy exceeds 90% across the board. The AE-RNN model achieves the most balanced and robust performance, outperforming conventional CNN-based architecture in detection and segmentation tasks while maintaining a high retrieval efficiency.

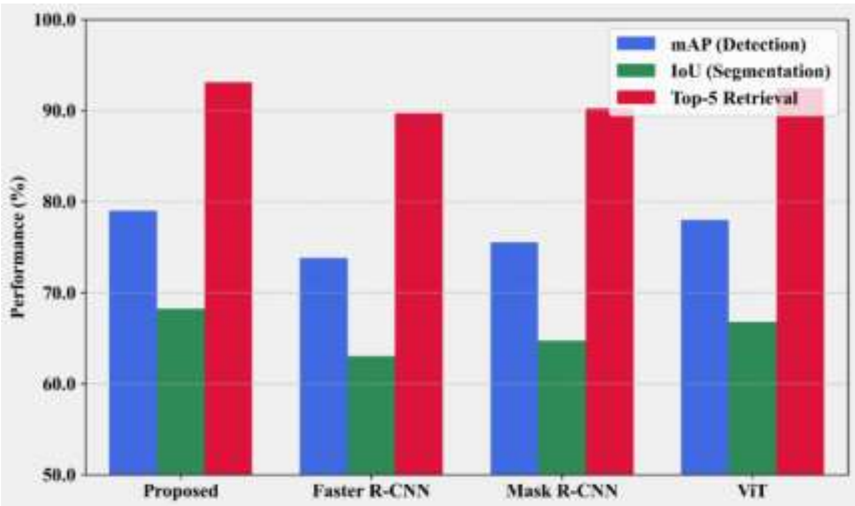

Fig.6: Model Comparison

Figure 7 illustrates the retrieval accuracy comparison among the proposed AE-RNN model, Faster R-CNN, Mask R-CNN, and ViT, using three key metrics: Top-1 Accuracy, Top-5 Accuracy, and Top-10 Accuracy. The proposed model achieves the highest performance across all three measurements, attaining approximately 87% in Top-1 Accuracy, around 96% in Top-5 Accuracy, and nearly 99% in Top-10 Accuracy. Faster R-CNN records a Top-1 Accuracy of 75%, with improvements observed in

Top-5 (88%) and Top-10 (93%) retrieval accuracies. Mask R-CNN delivers moderate outcomes, achieving 78% in Top-1 Accuracy, 91% in Top-5, and 96% in Top-10. The ViT model demonstrates relatively better retrieval accuracy than Mask R-CNN, with Top-1, Top-5, and Top-10 scores reaching approximately 80%, 93%, and 98%, respectively. The evaluation confirms that the AE-RNN model outperforms all other models, particularly in Top-1 retrieval accuracy, establishing its superiority for high-precision image retrieval applications.

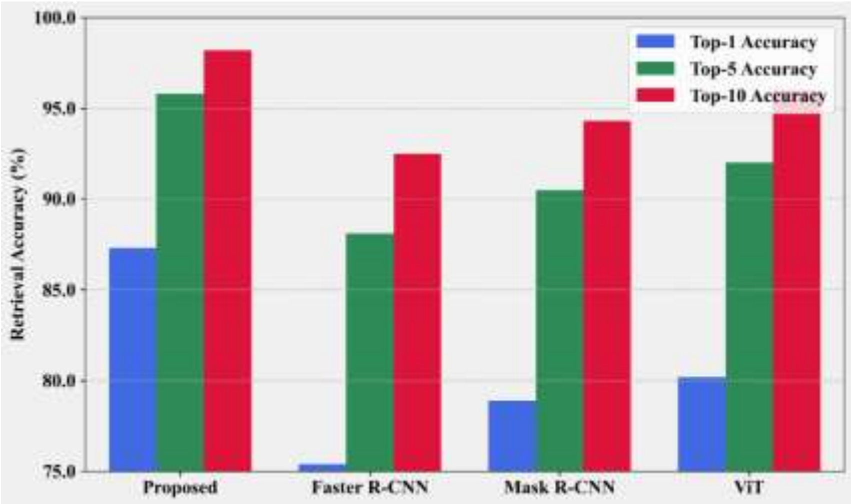

Fig.7: Received Accuracy

Figure 8 presents the Receiver Operating Characteristic (ROC) curves for four models: the proposed AE-RNN model, Faster R-CNN, Mask R-CNN, and ViT, in relation to their class discrimination capabilities. The graph plots the False Positive Rate (FPR) along the x-axis and the True Positive Rate (TPR) along the y-axis. The Area Under the Curve (AUC) metric serves as a key indicator of classification performance, with higher values reflecting stronger discriminatory power. Among all tested models, the proposed AE-RNN achieves the highest AUC score of 0.97, highlighting its outstanding accuracy in class distinction tasks. ViT follows with an AUC of 0.90, signifying solid classification reliability. Mask R-CNN achieves a moderate AUC score of 0.82, whereas Faster R-CNN records the lowest performance with an AUC of 0.74. These findings confirm that the AE-RNN model significantly outperforms conventional architectures by maintaining a high true positive rate and limiting false positives, thus affirming its superior effectiveness in classification contexts.

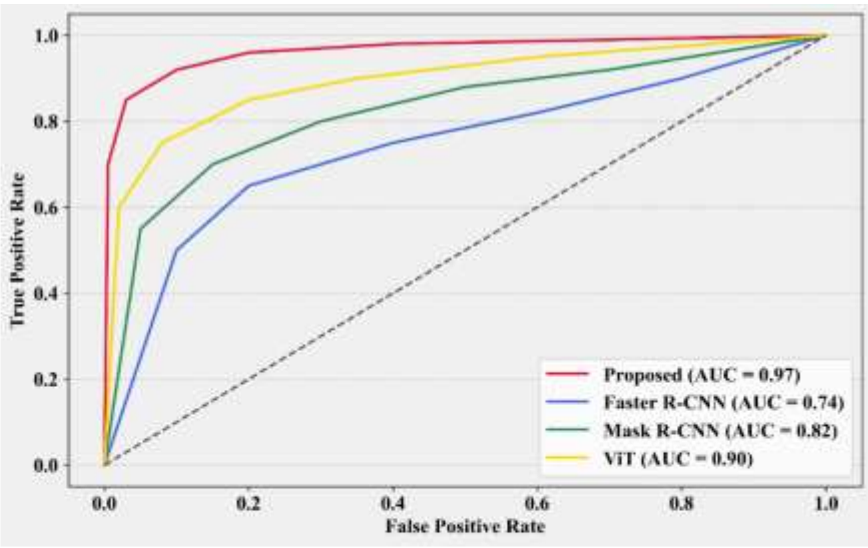

Fig.8: ROC Comparison

Figure 9 illustrates two performance graphs generated during the training process of a deep learning model over 100 epochs. The left-hand plot, depicting training accuracy, shows a consistent upward progression, ultimately reaching 0.97 (97%) by the final epoch. Concurrently, validation accuracy follows a similar trend, stabilising slightly below the training accuracy at approximately 0.94 (94%). This pattern indicates robust learning performance with minimal overfitting. The accompanying "Training vs. Validation Loss" graph reveals a corresponding trend in loss values, where the model initially records a high loss of around 0.8. As training progresses, a marked decrease occurs, with loss values reducing to approximately 0.05 by the hundredth epoch. The close alignment between the training and validation loss trajectories signifies that the model generalises effectively across datasets. The consistent balance observed between training and validation performance metrics throughout the training cycle confirms the model's stable learning behaviour and sound generalisation capability.

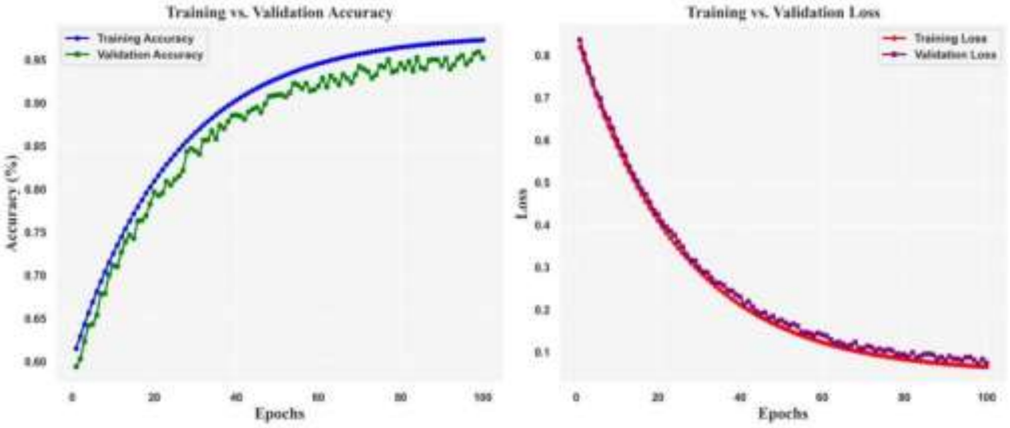

Fig.9: Validation Measures of Accuracy and Loss

The selection of the most appropriate artificial intelligence model for deployment within the fashion sector necessitates a comprehensive evaluation of both predictive performance and computational efficiency, as reflected in the comparative assessment table. Among the four examined models, AE-RNN, Faster R-CNN, Mask R-CNN, and ViT—the AE-RNN consistently outperforms its counterparts across all major evaluation dimensions. Specifically, it records the highest Accuracy (97.3%), Precision (96%), Recall (96.8%), and F1-Score (96%), confirming its reliability for classification and detection-related functions. In terms of object detection and segmentation capabilities, AE-RNN also secures leading values, achieving a mean Average Precision (mAP) of 80% and an IoU score of 70%.

Table 2

Consolidated Decision Matrix of AI Models for Sustainable Fashion Applications—Including Performance Metrics, AHP Weights, Normalised Scores, and Final Rankings

Criteria	Weight (%)	AE-RNN	ViT	Mask R-CNN	Faster R-CNN
Accuracy	20%	0.97(1.00/.20)	0.91 (0.94 / 0.188)	0.90(0.93/0.186)	0.88(0.91/0.182)
Precision	15%	0.96(1.00/0.15)	0.901 (0.94 / 0.141)	0.88 (0.92 / 0.138)	0.85 (0.89 / 0.134)
Recall	15%	0.97(1.00/0.15)	0.91 (0.94 / 0.141)	0.89(0.92/0.138)	0.85(0.88/0.132)
F1-Score	10%	0.96(1.00/0.10)	0.908(0.95/0.095)	0.88(0.92/0.092)	0.86(0.90/0.090)
Computational Efficiency	15%	High(1.00/0.15)	Medium(0.79/0.119)	Low(0.55/0.083)	Low(0.45/0.068)
Retrieval Accuracy	10%	96%(1.00/.10)	93% (0.97 / 0.097)	91%(0.95/ .095)	88%(0.92/ .092)
Detection (mAP)	5%	80%(1.00/.05)	78% (0.975 / 0.049)	77%(0.963/.048)	75%(0.938/.047)
Segmentation (IoU)	5%	70%(1.00/ .05)	68% (0.971 / 0.049)	64%(0.914/0.046)	62%(0.886/0.044)
AUC Score	5%	0.97(1.00/ 0.05)	0.90 (0.928/ 0.046)	0.82(0.845/0.042)	0.74(0.763/0.038)
Total Weighted Score	100%	1.000	0.905	0.868	0.827
Final Ranking	—	1st	2nd	3rd	4th

Furthermore, the model demonstrates exceptional retrieval performance, with Top-1, Top-5, and Top-10 accuracy levels reaching 87%, 96%, and 99%, respectively. In addition to its predictive excellence, AE-RNN exhibits notable computational efficiency, characterised by the lowest inference time (80 milliseconds), minimal model size (100 MB), and reduced computational complexity (55 GFLOPs), making it particularly suitable for real-time fashion supply chain applications. Its robust classification ability is further supported by a high Area Under the ROC Curve (AUC) score of 0.97. Conversely, although models such as Faster R-CNN and Mask R-CNN offer acceptable outcomes, they fall short in both predictive accuracy and resource efficiency. Consequently, based on the aggregated performance metrics and their weighted significance, AE-RNN attains the highest rank within the decision matrix, rendering it the most appropriate AI-based solution for fostering innovation, enhancing sustainability, and advancing operational responsiveness in the dynamic fashion industry.

5. Conclusion

Fashion manufacturing is undergoing a transformative shift through the integration of artificial intelligence, which addresses operational demands alongside sustainability challenges and ergonomic considerations. This study proposes a comprehensive AI-driven decision support system that combines predictive analytics with MCDM techniques to improve ergonomic outcomes while advancing ethical manufacturing practices and optimising production processes. AI contributes to enhanced manufacturing capabilities by forecasting market demand, facilitating automation in operations and resource allocation, and enabling sustainable decision-making that minimises waste, protects workforce welfare, and fosters organisational adaptability. Advanced personalisation engines, supported by AI and integrated with the AHP in retail contexts, facilitate virtual try-on technologies and recommendation systems, thereby improving consumer satisfaction. Concurrently, AI-based solutions in product development and logistics help reduce delivery timelines and mitigate inefficiencies within the supply chain. The collective findings highlight the strategic role of AI in enabling sustainable, human-centred innovation across the contemporary fashion industry. The continued advancement of artificial intelligence is expected to ensure the long-term viability of the clothing sector by strengthening operational efficiency and embedding ethical manufacturing methods grounded in ergonomic principles.

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