ITC INFOTECH

Business-friendly Solutions

Sustainable Material Attribution for
F&A Industry

Abstract - Material attribution is an integral part of product life cycle management. In the apparel fashion industry, material attribution activities are error prone because of their manual and monotonic nature. As a part of intelligent process automation for material attribution, we are proposing a model that uses deep neural networks to automate the classification of apparels based on attributes such as gender, category, subcategory, and color, when an image of an apparel is passed to the model. Our model assures process improvement by accurately extracting all the attributes in one go by using a computationally efficient algorithm that also minimizes the carbon footprint.

1. INTRODUCTION

The fashion and apparel (F&A) industry is an extraordinarily complex, dynamic, and competitive marketplace. The industry is dominated by powerful international brands as well as local brands that have significant loyalty. With the number of millennial consumers on the rise, which are highly influenced by social media, proliferation of e-commerce and cross-border commerce, the market is geared for growth despite slump during the covid years (2020-2021). The fashion industry was estimated to be around 2.5 trillion USD before the pandemic, providing livelihood for about three hundred million people around the world [1].

The value chain of product life cycle management in the F&A industry may be succinctly summarized as in Figure 1. Across each of the stages in the value chain, there are different personas that are faced with a plethora of problems. For instance, the merchandiser must predict consumer demand that is in tune with the latest trends with accuracy, which will be used by the designers. The designer must draw insights from disparate data sources including social media about the market, competition, customer preferences and costs to meet the design requirements. The product developer faces challenges in terms of managing changes in specifications, production bottlenecks, incomplete and incorrect data, and managing vendor related problems. The sourcing manager must ensure that the best source is chosen in terms of performance and cost, comply with regulations, select vendors, and efficiently manage shipping and delivery.

Figure 1: PLM value chain in F&A industry

Despite the slump, the industry is poised for a recovery though uneven. Retailers, manufacturers, and brands must cater to the rapidly changing preferences of the customers by launching innovative new products at a great pace. Figure 2 summarizes the paradigmatic shift in the focus of retail business, from selling what is made to making what is sold. The focus has shifted from retailer centric to customer centric. Smart and digital manufacturing in F&A has greatly fueling this shift in focus, thereby facilitating short production cycles, reduction of waste, unplanned downtime, delays, defects, and rejections.

Figure 2: Paradigmatic Shift in Retail Business

However, F&A industry has the dubious reputation of being one of the top polluting industries along with oil, plastic, paper, and compost. Technology has enabled access for cheap clothing which get discarded quickly. Astronomical volume of clothes goes unsold with no regulation around methods of recycling. The long-term environmental impact of this reckless production and mindless discarding of clothes is proving expensive for sustenance. Figure 3 is just a speck of a sample of the amount of waste generated by the F&A industry.

Figure 3: A dump yard of readymade garments in India

ESG (environment, social and governance) risk is looming large on the sustainability mandate on the F&A industry[14]. Evidence such as report from IHS Markit [15] estimate that the F&A industry accounts for about 10% of global greenhouse gas emissions: that a pair of jeans requires 1800 gallons of water and 3 out 5 fast fashion garments end up in landfills within one year of purchase. With the regulations to control ESG risk becoming very stringent, F&A companies face significant threats of dwindling investments, losing their competitiveness, sustainability, and profitability.

While a lot of process improvements backed by technological advancements can help address the sustainability mandate, we at ITC Infotech India Ltd., advocate the adoption of sustainable PLM as a key first step to foster sustainability. Adoption of product life cycle management (PLM) strategies have helped in the automation of most of the processes in the value chain. Across each of the stages in the PLM value chain, statistical machine learning and mathematical programming-based models can help improve the processes by ushering in greater accuracies like demand forecasting [2], [3], [4], sales forecasting [5], [6] sales optimization [7], optimal supplier selection [8], [9], [10], [11] optimal sourcing [12], optimal routing [13], to name a few. Intelligent fashion is catalyzing the digital transformation of F&A industry with the help of artificial intelligence and data science. The various facets of intelligent fashion are summarized in Figure 4.

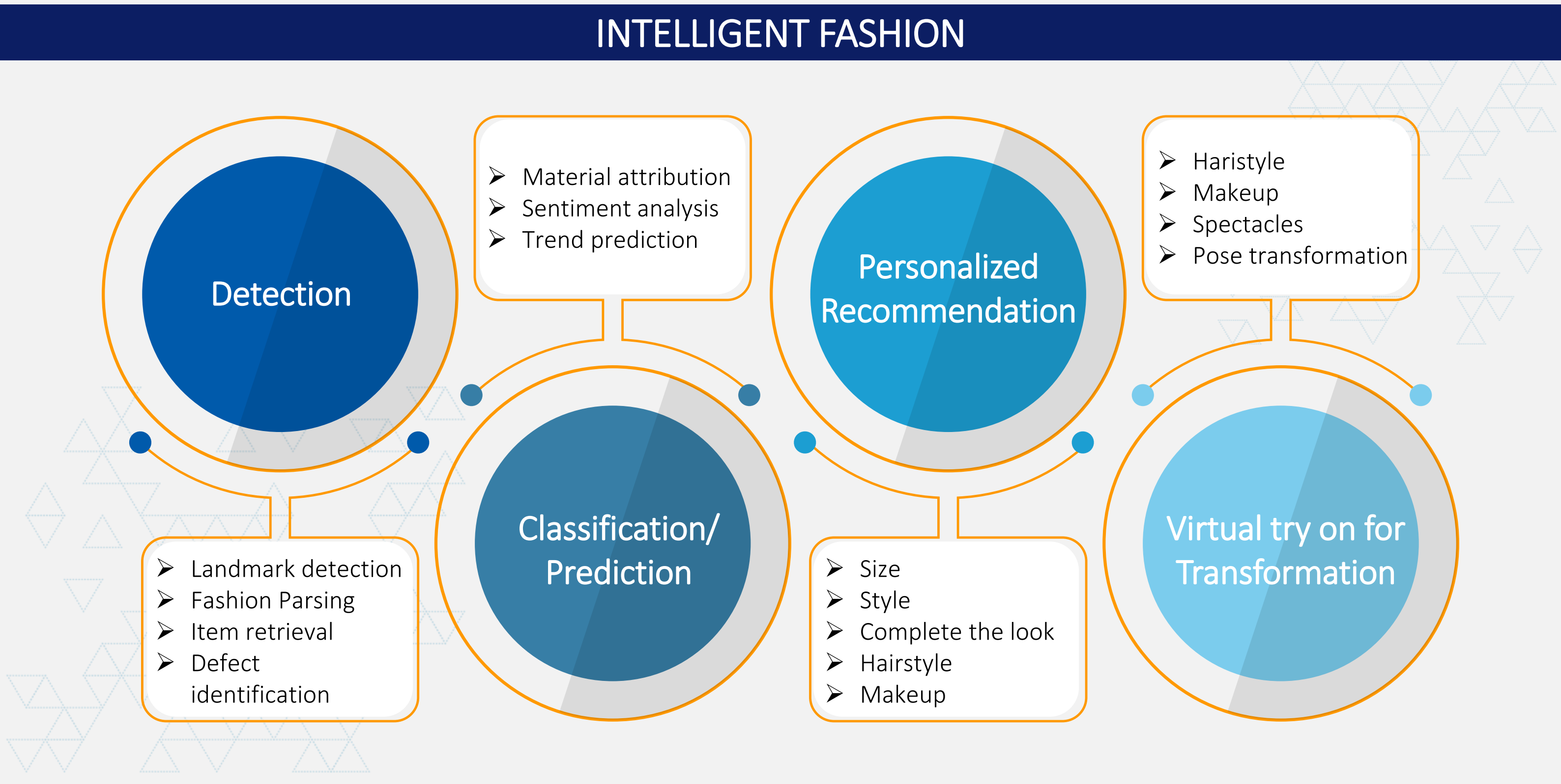


Figure 4: AI Applications for Intelligent Fashion

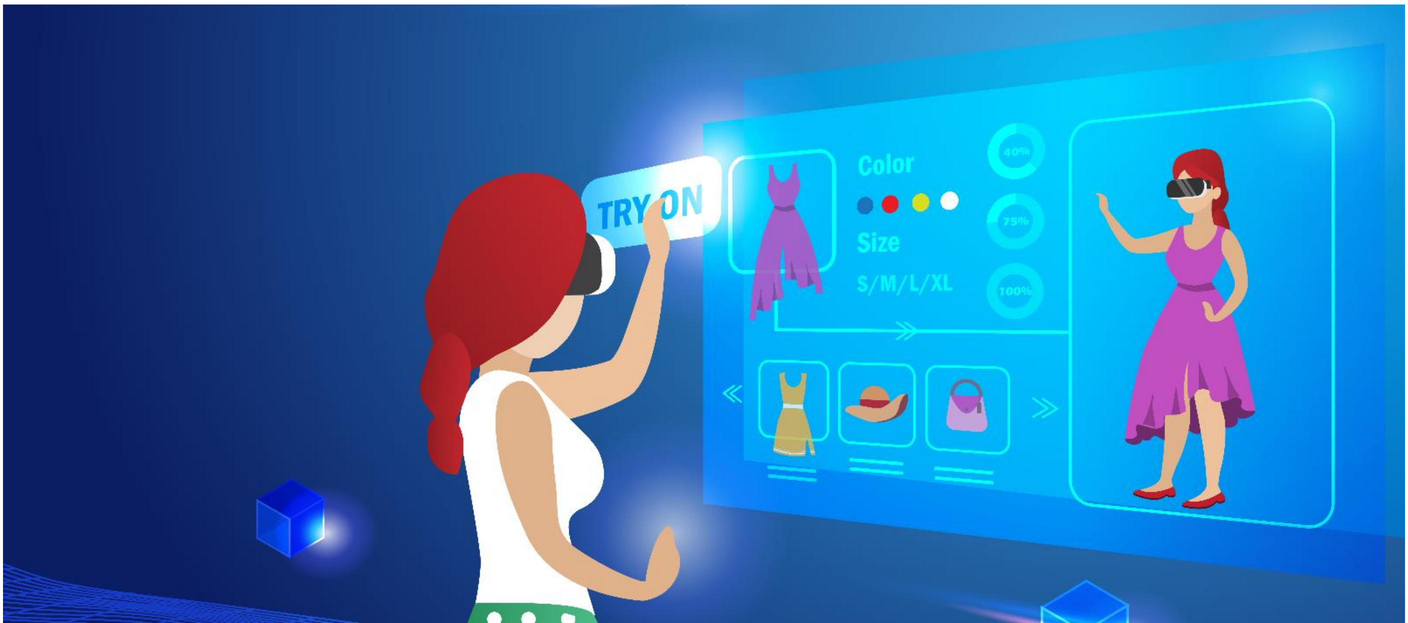
Adoption of AI/ML to aid material attribution can prove counterproductive if the algorithms are computationally costly adding to the carbon footprint generated by the industry by significantly reducing wastage and rejection. We at ITC Infotech India Limited, have engineered a deep learning-based solution that is both light weight and accurate. This solution was presented at the Microsoft Workathon 2021, where we finished as one of the top four contestants. Motivated by the sustainability mandate governing the F&A industry (as discussed in Section 1), we presented a computationally efficient algorithm that is highly scalable both vertically (to incorporate more attributes) and horizontally (to incorporate fashion from multiple ethnicities and cultures). We were also motivated to fill the existing gap in research that does not consider the sustainability aspect (as mandated by regulation) when designing the algorithms for multi-label classification for material attribution of fashion apparels.

AI has been used to solve several real-world problems in the F&A industry since long. One of the earliest reviews of AI applications in the F&A industry was done by Guo et. al [16] in 2011. The authors systematically reviewed and categorized the AI applications in the apparel industry into four categories namely apparel design, manufacturing, retailing and supply chain. The authors concluded that the work up to the point of review was mostly confined to analyzing the limitations of previous studies and research challenges. A recent and detailed review of 149 papers from Scopus and Web of Science, which contributed to AI applications in fashion industry was done by Giri et.al [17] in 2019. The authors opined that the research was scattered and mostly confined to applications in the various stages of supply chain. The authors classified the articles based on the methods, stages of supply chain, business-to-business (B2B), and business-to-consumer (B2C) and identified gaps in research that could be addressed in future.

An image process and AI-based approach for quantifying the yarn mass parameters like hairiness, diameter and mass, yarn production characteristics like snarl length, number of cables, fiber orientation and porosity was presented in [18]. Work based on computer vision on fashion has been reviewed in detail in [19] where the authors have reviewed over two hundred major fashions under topics landmark detection, retrieval and parsing, attribute recognition, style learning, popularity prediction, recommendation, and physical simulation. More recently, Seyed et. al [20] reviewed over 580 papers categorized under twenty-two fashion related tasks. Specifically, the authors reviewed sixty-nine articles published between 2011-2021 under the fashion categorization. The categorization problem specifically deals with grouping F&A pictures at an extremely high level, say, a shirt, dress, pants etc. This belongs to the single label prediction class of problems. The authors also reviewed fifty-eight articles published between 2011-2021 that addressed the attribute recognition problem. The attribute recognition problem is a multi-label classification task. The multiple attributes could be color, style, pattern, material, texture, to name a few. We refrain from discussing the other vision-based tasks in fashion that are reviewed by the authors in [20] to confine ourselves to the focus of this paper - namely the multi-attribute or multi-label prediction problem. However, we encourage readers to refer the above paper to better appreciate the breadth and depth of research opportunities replete in fashion for applications of deep learning and computer vision.

To the best of our knowledge based on extant literature review, material attribution in F&A industry involving multilabel classification is still a challenging problem. The existing methodologies are very heavy and need a humongous amount of data. The F&A industry is already finding it very challenging to meet sustainability standards and regulations [21] [22] [23]. A computationally costly model can pose further damage to the sustenance mandate imposed on the F&A industry.

Our model is a refined version of ResNet50 that can predict multiple labels in one go, though it is trained on relatively less data. This model is combined with the color detection model to give the final score for classification. This model is computationally efficient and can positively contribute to fostering the carbon negative mandate of the F&A industry.



2. DATA ANALYSIS

a) Source of Data

The data used for this use case is images of apparel (mostly western wear). Data is collected from multiple open sources like Kaggle, ecommerce portals and through web scraping. The quality of images used are of 300 DPI across multiple image formats (jpg, jpeg, png, gif, tiff). The data contained eighty different patterns with most of them falling under the “Solid” group. Figure 3 depicts the distribution of top ten patterns found in the data. The broad category of the photos are bottom wear and top wear where the classes are almost balanced as depicted in Figure 4. Figure 5 shows the distribution of the sub-categories and Figure 6 depicts a sub-set of representative images containing the categories and sub-categories. To train the model, the input file containing the various attributes of the apparel in a .csv format was utilized as shown in Table 1.

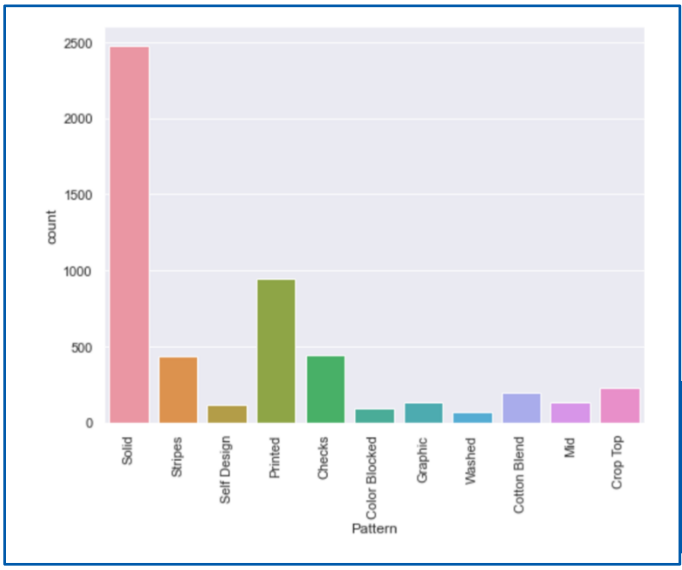


Figure 5: Distribution of Patterns

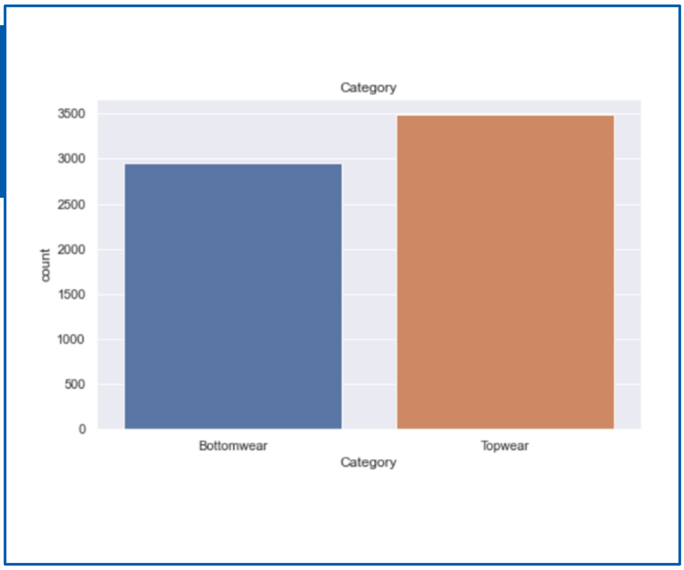


Figure 6: Distribution of categories

Image Name	Gender	Category	Sub-Category	Sleeve Type	Collar	Pattern
Image1	Women	Bottomwear	Trousers	NaN	NaN	NaN
Image2	Men	Bottomwear	Pyjamas	NaN	NaN	Graphic
Image3	Men	Topwear	Shirt	Full Sleeve	Regular	Stripes
Image4	Men	Topwear	Jacket & Coats	Full Sleeve	Round	Solid
Image5	Men	Bottomwear	Pyjamas	NaN	NaN	Check

Table 1: Sample input csv file

b) Number of Records

A total of around six thousand unique samples have been collected, out of which there are five hundred samples for each subcategory. The data has been augmented using standard augmentation techniques described below to create around thirty thousand samples.

Some of the augmentation techniques applied for increasing the sample size for training include:

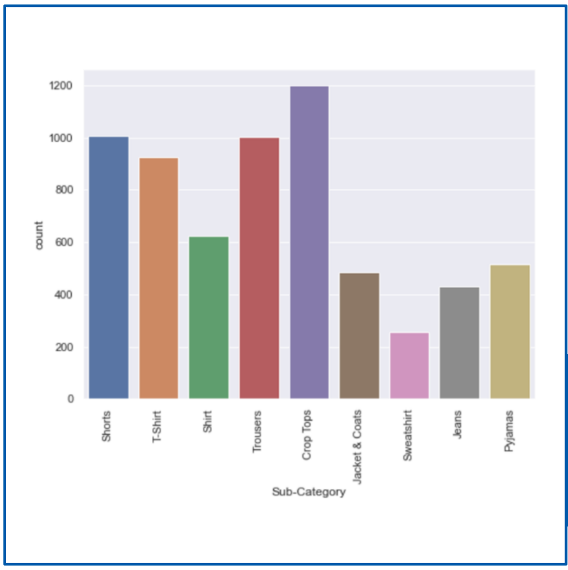
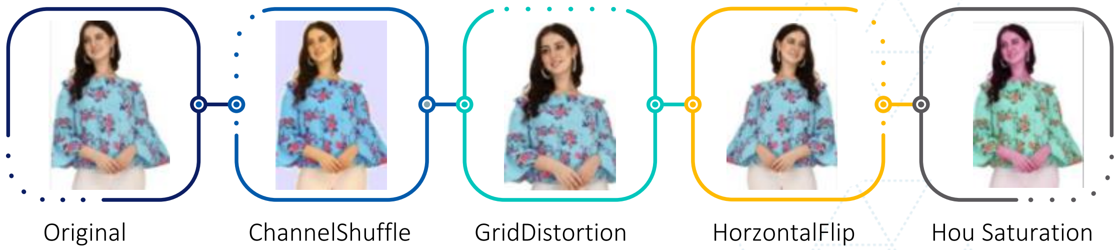


Figure 7: Distribution of sub-categories

Figure 8: Sample images containing categories and sub-categories

- **Channel shuffle:** Randomly rearranges the channels of RGB image.
- **Grid distortion:** Changes the grid points to distort the images randomly
- **Hue saturation value:** Randomly changes the Hue Saturation Value of the images.
- **Horizontal flip:** Flips the rows and columns of the image horizontally.



c) Pre-processing

Further pre-processing of the images was performed using techniques like skewness correction, image resizing, noise removal and standardization of image format. As some of the attributes were category specific to a group, those attributes have been treated as negative class. For example, sleeve type and collar are not applicable for Bottom wear category, so they are treated as negative class.

d) Exclusions

Around 1500 images with duplicate filenames, invalid or corrupted images and mismatched filenames in the input csv file were removed. Furthermore, attributes with less than 10% of the entire data have been excluded, to avoid misclassification. The attributes removed were either void or one of a kind (e.g., washed, animal print, machine wash, Halter neck, clean look etc.,). This finally resulted in a dataset with 24,500 images.

e) Sampling Methodology

We used a stratified random sampling approach to create a balanced dataset encompassing all categories, sub-categories, factor for training the model.

3. ATTRIBUTION MODELING TECHNIQUES

Apparel attribution is a multi-label classification problem where multiple features of the apparel which includes gender, category, subcategory, pattern, sleeve type, fit and the color are used for identification. Our solution combines two models – the first model detects the color of apparel, and the second model detects the remaining features. The color detection model is horizontally scalable to use in other industry use-cases. The material attribution model is vertically scalable to incorporate more attributes and categories. The idea is to keep the model as generic as possible to cater to adjacencies.

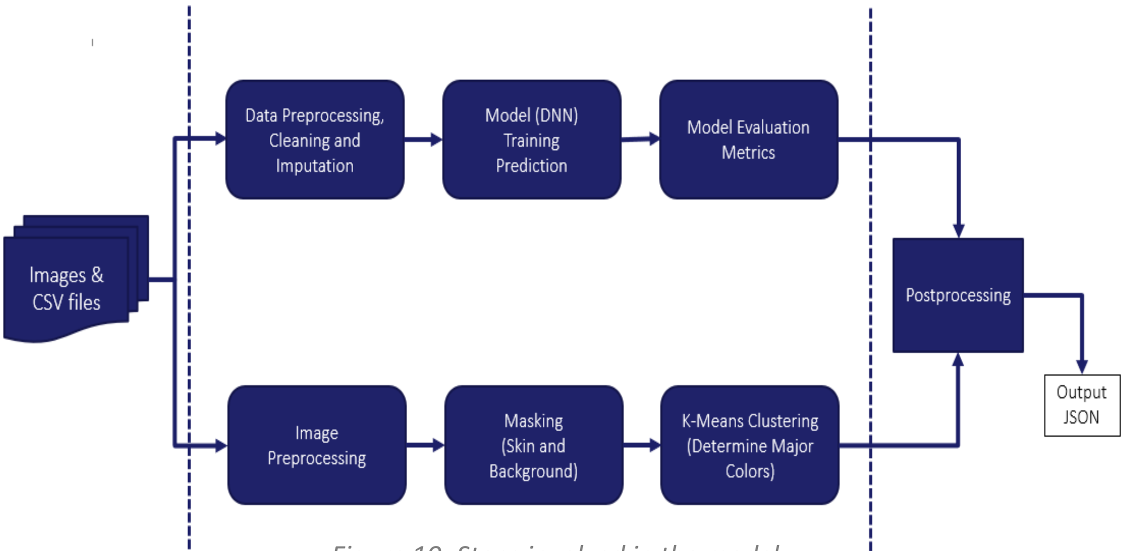


Figure 10: Steps involved in the model

a) Color Detection Model

The color detection model has three steps:

i. Background removal

For background removal, an improvised DeepLabv3+ model [25] was used for assigning semantic labels to every pixel in the input image. We improvised this state-of-the-art deep learning model by adding a simple decoder module to refine the segmentation. Atrous Spatial Pyramid Pooling (ASPP) and Depthwise separable convolution operations have been used to improve model performance. The hyper-parameters tuning was not performed at this step, as the goal was to pretrain the model on ImageNet for semantic segmentation.

ii. Skin color masking

For skin masking, computer vision techniques have been used. The HSV (Hue, Saturation, Value) is the model used to represent the RGB color in alignment to the human perception. The Hue denotes the dominance of the wavelength for the color, Saturation denotes the shades of the color and value indicates the intensity of the color.

By using the optimized thresholds values for the HSV values that represented the skin color, binary images were created by filtering out pixels – pixels within the threshold were made white else they were made black.

iii. Color detection

Here the objective was to group the colors and get the top two colors of the apparel. K-means clustering was used for this purpose. The color pixels were grouped, and the biggest group color was returned as output. In Figure 9, the steps for color detection model are depicted for visual comprehension.

Figure 11: Logical flow for apparel color detection

b) Material Attribution Model

The key features of apparel like gender, category, subcategory, pattern, sleeve type and fit are identified by the material attribution model. There are multiple ways to classify these attributes that are briefly discussed below along with their merits and demerits to justify our choice of modeling approach. Figure 10 depicts the logical flow of the material attribution model.

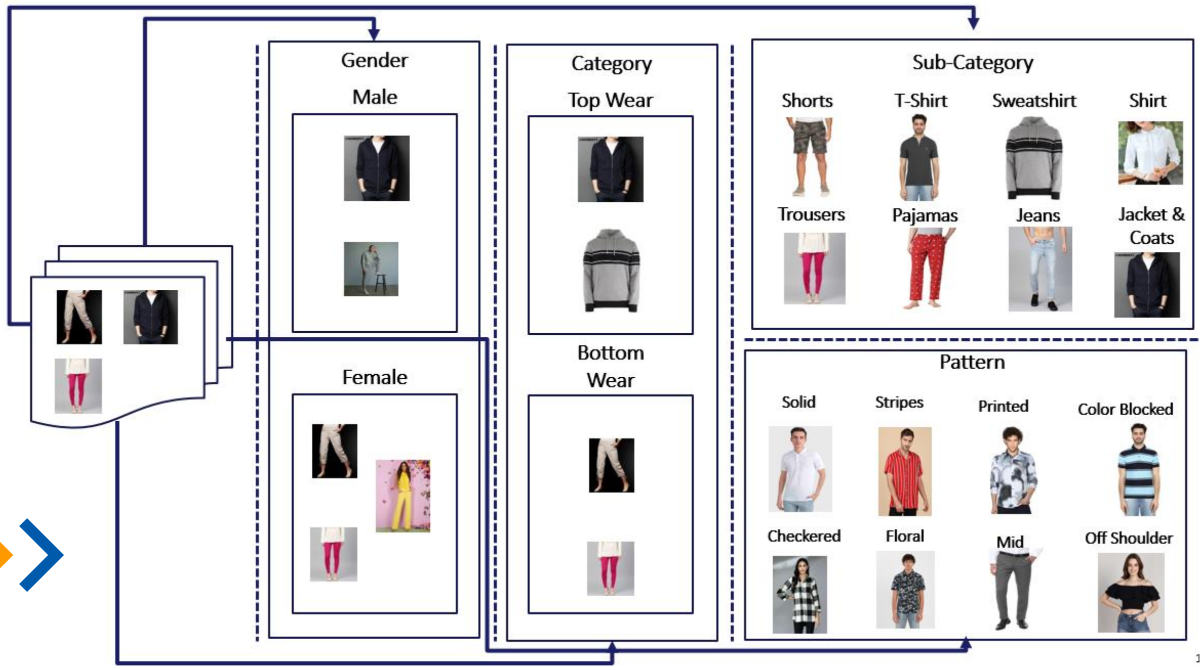


Figure 12: Logical flow of the material attribution model

Prior to explaining our model, it is appropriate to summarize the rationale for our model approach. When there are multiple attributes to be identified, it is natural to think that each attribute would have to be modeled individually to achieve high accuracy. However, this approach can exponentially increase the model size, reduce the computation speed and may not be scalable when new features are encountered. Another approach to model this problem is the hierarchical classification model, where a single model is used to classify the attributes in a hierarchical manner/. Demerits of this approach include longer computation time and inability to scale.

Our solution approach

To circumvent the drawbacks associated with the other modeling approaches, we chose to improvise a deep learning model that can classify the multiple labels or attributes that define a class in one shot. Multi-label classification model uses multi-label binarization (MLB) technique, where all the unique classes will be binarized. The output layer of the neural network is these binarized labels. We trained an improvised version of Resnet50 is the Deep Learning model with twenty thousand images for twenty epochs. The sigmoid loss function was used in the last layer of the network to obtain the class probabilities. Binary cross entropy loss function and adam optimizer were used for building this model. ResNet is well documented, and we point the readers to [26] for further details. Figure 11 represents that there can be one or more features for a sample data, which can be detected by setting threshold to the probabilities of the output nodes. By setting a threshold to these probabilities, the output nodes which are having probability more than the threshold are identified as the features of the sample image. This model performs better than other modeling approaches both in terms of accuracy and computational efficiency.

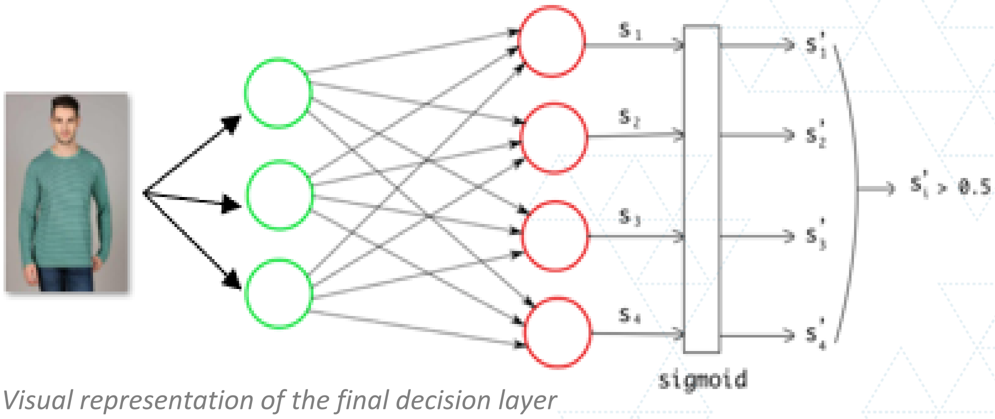


Figure 13: Visual representation of the final decision layer

c) Combined Model output

The output of both color detection model and material attribution model are combined and written out into a Json file. This file can be further consumed by applications for further processing to aid automation.

4. MODEL PERFORMANCE

Standard evaluation metrics were used for verifying the model performance:

- ❖ **Classification Accuracy:** It is the ratio of the number of correct predictions to the total number of predictions made for a dataset. In our case the accuracy turned out to 95%.
- ❖ **Hamming Loss:** The Hamming loss is the fraction of labels that are incorrectly predicted. Lower the Hamming loss, better the accuracy. Our model had a Hamming Loss of 0.0083.
- ❖ **Confusion Matrix and Classification Report:** A confusion matrix is a table that shows the number of correct and incorrect predictions made by the model compared with the actual classifications in the test set. Using the confusion matrix, we can determine the performance metrics such as Precision, Recall, F1 score and accuracy of the model. Though the confusion matrix is discussed everywhere, it is rather confusing. Hence, it is worth noting down here for ready reference as shown in Table 2, other performance measures like precision, recall and F1 score are derived. The model performed well both at the overall level as well as the attribute level identification. The model results are summarized in Table 3.

Table 2 : Confusion matrix

	Actual Class	
Predicted Class	Positive	Negative
Positive	True positive (TP)	False positive (FP)
Negative	False negative (FN)	True negative (TN)

Precision = TP/(TP+FP)
Recall = TP/(TP+FN)
F1 Score = (2*Precision*Recall)/(Precision+Recall)

Table 3: Model Performance Report

	Precision	Recall	F1-score
Overall	0.98	0.95	0.96
Class-wise	0.97	0.81	0.86

We have not presented the results of the comparative performance of other models here. As they were discarded on the grounds of their drawbacks, it is deemed redundant to discuss their performance here.

5. CONCLUSION AND DIRECTIONS FOR FUTURE WORK

In this paper, we proposed an improvised deep learning model that is not only able to identify the color and other attributes of the apparel accurately but is also computationally efficient. It will be helpful to address the ESG mandates for the F&A industry in terms of their sustainability commitments. This model will be very handy in automating the material attribution work in the PLM value chain in the F&A industry. In terms of future work, this model can easily be scaled to include ethnic wear where more attributes may have to be accommodated. This model may be horizontally scaled to identify the material attributes in industry 4.0.

6. REFERENCES

- Imran Amed, Anita Balchandani, Achim Berg, Saskia Hedrich, Jakob Ekeløf Jensen, Leila Le Merle, and Felix Rölkens, *"State of Fashion 2022: An uneven recovery and new frontiers,"* McKinsey, 2021.

- S. Nakamura and Y. Kodono, *"Fuzzy reasoning demand forecasting model by using meteorological factors — Case of apparel shop,"* The 6th International Conference on Soft Computing and Intelligent Systems, and The 13th International Symposium on Advanced Intelligence Systems, 2012.

- A. Bruzzone, F. Longo, L. Nicoletti, A. Chiurco and C. Bartolucci, *"Multiple Forecasting Algorithms for Demand Forecasting in the Fashion Industry,"* 2013, 8th EUROSIM Congress on Modelling and Simulation.

- F. Saito, H. Yamashita, H. Sasaki and M. Goto, *"Machine Learning for Demand Prediction of Seasonal Second-hand Fashion Items Based on Prior and Fine-tuning Prediction Models,"* IEEE 12th International Workshop on Computational Intelligence and Applications (IWCIA), 2021.

- C. Giri, S. Thomassey, J. Balkow and X. Zeng, *"Forecasting New Apparel Sales Using Deep Learning and Nonlinear Neural Network Regression,"* International Conference on Engineering, Science, and Industrial Applications (ICESI), 2019.

- P. C. L. Hui and T.-M. Choi, *"Using artificial neural networks to improve decision making in apparel supply chain systems,"* Information Systems for the F&A industry, Elsevier, 2016.

- N. B. Ganhewa, S. M. L. B. Abeyratne, G. D. S. Chathurika, D. Lunugalage and D. De Silva, *"Sales Optimization Solution for Fashion Retail,"* 3rd International Conference on Advancements in Computing (ICAC), 2021.

- Akman, G.; Piskin, H, *" Evaluating green performance of suppliers via analytic network process and TOPSIS,"* Journal of Industrial Engineering, 2013.

- Choi, T.M, *"Optimal apparel supplier selection with forecast updates under carbon emission,"* Comput. Oper. Res., 2013.

- Peng Jia, Kannan Govindan, Tsan-Ming Choi, and Sivakumar Rajendran, *"Supplier Selection Problems in Fashion Business Operations with Sustainability Considerations,"* Sustainability, 2015.

- Shen, L.; Olfat, L.; Govindan, K.; Khodaverdi, R.; Diabat, A,
  "A fuzzy multi criteria approach for evaluating green supplier's performance in green supply chain with linguistic preferences," Resour. Conserv. Recycl., 2013.

- Elisa Arrigo,
  "Global Sourcing in Fast Fashion Retailers: Sourcing Locations and Sustainability Considerations," Sustainability, 2020.

- R. Tanaka, A. Ishigaki, T. Suzuki, M. Hamada and W. Kawai,
  "Shipping Plan for Apparel Products Using Shipping Record and Just-in-Time Inventory at a Logistics Warehouse," 7th International Congress on Advanced Applied Informatics (IIAI-AAI), 2018.

- Achim Berg, Karl-Hendrik Magnus, Sara Kappelmark, Anna Granskog, Libbi Lee, Corinne Sawers, Poorni Polgampola, Morten Lehmann, Holly Syrett, Gizem Arici, *"Fashion on Climate,"* McKinsey, 2020.

- Y. A. C. C. E. W. Sara Abbasi,
  "Fast Fashion: Why Brands Need to Consider ESG to Slow Down," IHS Markit, 2021.

- ZX Guo, WK Wong, SYS Leung, Min Li,
  "Applications of artificial intelligence in the apparel industry: a review," Textile Research Journal, 2011.

- C. Giri, S. Jain, X. Zeng and P. Bruniaux,
  "A Detailed Review of Artificial Intelligence Applied in the F&A industry," IEEE Access, 2019.

- V. Carvalho, F. Soares and R. Vasconcelos,
  "Artificial intelligence and image processing based techniques: A tool for yarns parameterization and fabrics prediction," EEE Conference on Emerging Technologies & Factory Automation, 2009.

- Wen-Huang Cheng, Sijie Song, Chieh-Yun Chen, Shintami Chusnul Hidayati, and Jiaying Liu,
  " Fashion Meets Computer Vision: A Survey," ACM Computing Surveys, 2021.

- Seyed Omid Mohammadi, Ahmad Kalhor,
  "*Smart Fashion: A Review of AI Applications in the Fashion & Apparel Industry*," https://arxiv.org/abs/2111.00905v2, 2021.

- Christine Ro,
  "Can fashion ever be sustainable?," https://www.bbc.com/future/article/20200310-sustainable-fashion-how-to-buy-clothes-good-for-the-climate, 2020.

- Kenneth P. Pucker,
  "The Myth of Sustainable Fashion," https://hbr.org/2022/01/the-myth-of-sustainable-fashion, 2022.

- Gazzola, P.; Pavione, E.; Pezzetti, R.; Grechi, D,
  "Trends in the Fashion Industry. The Perception of Sustainability and Circular Economy: A Gender/Generation Quantitative Approach," Sustainability, 2020.

- Buslaev, Alexander and Iglovikov, Vladimir I. and Khvedchenya, Eugene and Parinov, Alex and Druzhinin, Mikhail and Kalinin, Alexandr A,
  "Albumentations: Fast and Flexible Image Augmentations," Information (https://www.mdpi.com/2078-2489/11/2/125), 2020.

- Soumik Rakshit,
  "Multiclass semantic segmentation using DeepLabV3+," (https://keras.io/examples/vision/deeplabv3_plus/), 2021.

- K. He, X. Zhang, S. Ren and J. Sun,
  "Deep Residual Learning for Image Recognition," IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.