Leather Fashion Colours Forecasting Using Artificial Intelligence

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Abstract

Colours serve as an embodiment of preference, choice, identity, expression and aesthetics. The colours of the products, we carry have the power to represent ourselves. The strategic choice of colours in product manufacturing plays a pivotal role in elevating the appeal, identity, style and value of the product. In the Leather context, the end products are highly dependent on the fashion colour trends as they need validation from the fashion industry. Seasonal colour forecasting namely Fall Winter (FW) and Spring Summer (SS) play a huge role in leather industry as it acts as the guidelines for the manufacturers that helps them to align their productions with global consumer preferences and demands. It also indirectly aids in streamlining the supply chain management by contributing to the enhanced logistics. The primary objective of the work is to build a model that predicts the seasonal colour trends by taking multiple data sources having historical colours.

The approach involves optimization algorithm namely Hungarian matching to segregate the input based on minimum Delta E difference and feeding the segregated colour inputs to Deep Learning model that forecasts the upcoming colours of the season. The outputs from different data source models are further fed to an ensemble ML technique namely Consensus-Dispersion Weighted Ensemble that fuses the output from different data source models to a unified output that has improved accuracy.

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The findings demonstrate that the AI-driven models can effectively learn slow seasonal colour transitions, and can ease the early prediction of emerging hues which can benefit the manufacturers and designers. It overcomes the manual colour prediction systems as they can be biased due to human perceptions and subjectivity. This work significantly contributes to the leather sector by enabling to make informed decisions early in the product development. The system supports better material planning, reduces wastage, and strengthens competitiveness by offering scientifically grounded future colour predictions catering to evolving consumer preferences and global fashion dynamics.

Key Words: Fashion Colour forecasting, Deep learning, GRU, Artificial intelligence, Fashion analytics, Fashion trend prediction, Leather Fashion Colours

1. Introduction

The term “Fashion Colours Forecasting” may sound superficial to a leather manufacturing sector as it involves rigorous activities like tanning, dyeing, processing and other activities associated with leather but a product manufactured in the wrong shade or not aligned with the current trend is a potential waste generated. A leather product in the right shade defines the meagre difference between a bestseller and an overstock.

Fashion colour plays a major role in leather products as we humans are more influenced by colour than any other features like shape, texture or even over quality. The human

brain processes the colour in less than 100 milliseconds whereas processing of other attributes like shape and texture takes significantly longer duration. Neuroscience research proves that up to 95% of purchasing decisions are made subconsciously which are driven by emotion rather than logic. (Zaltman, 2003).

Leather unlike fabric involves multiple stages in processing from raw hide to finished leather which makes the major forecasting agencies and colour authorities release their predictions at least 18-24 months in advance and it is released generally in collections named as Spring Summer (SS) and Fall Winter (FW). The proposed research work aims to predict these forecasts using the historical predictions made by the major leather specific trend forecasting agencies.

Colours in any fashion not just leather usually maintain patterns like cyclic repetition of colours, dominance of classical colours over Fads (Abbasi, 2013). The proposed research work makes use of one such pattern which is exclusive to leather i.e., the hues of leather transits gradually rather than abruptly. This pivotal characteristic is used predominantly in feeding the input data to the model that uses the segregated similar colours over the past as the input.

The traditional / manual colour forecasting is a labour intensive, subjective and at times cognitive biased due to human intervention (Anilkumar & Baskaran, n.d.) and the fact that forecasting has outgrown human cognitive abilities in a data intensive, fast moving and globally connected marketplace has given rise to an AI based leather fashion colour forecasting. The major advantage of AI driven colour forecasting lies in its ability to systematically analyse vast historical datasets and extract the patterns or key points in forecasting the colour palettes. Nadeem et al. (2022) utilized web-scraped fashion image data and applied ARIMA models to forecast the future frequency of 45 trending colours. Jiju et al. (2024)

demonstrated the effectiveness of machine learning and deep learning techniques in analysing fashion data for tasks including colour extraction, trend analysis, and forecasting. In a similar vein, our work examines the evolution of leather fashion colours by leveraging data-driven methods to identify temporal patterns thereby proposing an effective and efficient model exclusively for the leather industry to forecast the upcoming seasonal fashion colour trends.

2. Methodology

The proposed methodology consists of four major stages:

2.1 Data Collection

Historical leather fashion colours predicted over past years by prominent leather colour/trend forecasting agencies were used for this purpose. The proposed model focuses on the Fall Winter (FW) variant and it aims to predict the F/W variant of 2026. Three major sources were chosen and named as Primary, secondary and tertiary with respective importance. Primary source contributes 9 years of historical colour data, secondary source includes 16 years of colour data and the tertiary source has the colours of 2025 that was most searched on Instagram. The dataset is in the form of colour palettes consisting of 27-35 colours in each year. The colours are represented in the CIELAB format because of its relevance to human visual perception.

2.2 Data Pre-processing

The Fashion colours of each year are pre-processed with an optimization algorithm namely Hungarian matching to segregate the input palette based on minimum Delta E difference. The Delta E difference between each and individual colours of palettes of all the years starting from the oldest year available is calculated. Following which, the Hungarian Matching algorithm is applied, that results in the alignment of similar colours across palettes of different years of the sources namely primary and secondary (Fig1).

Fig1-Historical data of primary and secondary sources rearranged using Hungarian matching algorithm

The vacant cells occur due to two reasons, namely missing data and the non-occurrence of the similar colours in the respective years. As the Similar colours of each years are to be fed to the Deep learning model individually to identify how these colours have evolved over the years and how they would be for the upcoming year to be

Fig2-Imputed historical data of primary and secondary

2.3 Deep Learning Model

The similar colours segregated and imputed by the Linear interpolation technique are fed individually to a deep learning model. Although the input data is compatible with multiple architectures like LSTM, GRU, MLP, Transformers. GRU and MLP are chosen, as our data

predicted, it is essential to fill in the blank spaces for the deep learning model to learn the colour evolution. To address this issue, Linear imputation technique has been used. The Linear Imputation technique handles missing data using the linear relationship of the available data in the neighbourhood.

size is highly limited and the concept of short-term temporal relationship is more relevant to our data and leather fashion trends than the long-term dependencies which are the focal point of architectures like LSTM and transformers. The Architectures of GRU and MLP are applied individually to primary and secondary data excluding the tertiary data as it possesses only the previous year palette.

2.3.1 GRU (Gated Recurrent Unit)

Gated recurrent Units (GRU), an advanced variant of RNNs (Recurrent Neural Networks) primarily introduced by Cho et al. in 2014 performs exceptionally well for discovering temporal relationships of small sized sequential

data. Its gating mechanism enables it to selectively retain or discard information from sequential. GRU learns the colour evolution over the past years, the intricate colour dependencies and how a colour could evolve in the upcoming year from the past years.

2.3.2 MLP (Multi-layer Perceptron)

Multi-Layer Perceptron (MLP) is a feed forward neural network that works in a single direction. Unlike RNNs, the MLPs do not have memory to capture the sequential dependencies. However, it still produces good results when the data size is extremely small and relationships in the input data is very straightforward making them a better choice for the inputs that may not require the complex hidden dynamics of architectures like GRU (Zhang et al., 2020).

2.4 Postprocessing

To integrate the outputs produced from models that were applied to the primary and secondary sources with the tertiary source while preserving the hierarchical weightage of the primary source, we introduce an ensemble ML technique named as Consensus-Dispersion Weighted Ensemble. The aim of this methodology is to fuse the output

Fig 3 -Hungarian matched colours produced from GRU models of primary and secondary

with the tertiary colour palette

from different data sources to a unified output that has an improved accuracy. This approach sets follows six step procedure which includes consensus mean computation, dispersion quantification as the absolute deviation of each prediction from the consensus with regularization parameter ε, inverse dispersion calculation to establish confidence scores, priority weight application using predefined coefficients to maintain hierarchy, weight normalization to ensure unit sum constraint, and finally weighted linear fusion of source predictions. The final output is a single L,a,b coordinates representing the colours fused from the different sources.

3. Result & Discussion

The Colours produced for Primary and Secondary sources along with the Tertiary source is aligned by Hungarian matching algorithm as shown in (Fig 3) for GRU model and (Fig 4) for MLP model. These aligned colours when exposed to Consensus-Dispersion Weighted Ensemble method produce a unified colour palette that maintains the hierarchical weightage of the sources as shown in (Fig 5). This palette also represents the final Fall/Winter colour collection of 2026 using the historical data of up to 2025. In order to prove the efficacy of the results, the actual colour palette of 2026 F/W collections of the primary source which was given the highest-level importance throughout our architectures was compared against the results produced by both the architectures as shown in (Fig 6).

Fig 4-Hungarian matched colours produced from MLP models of primary and secondary

with the tertiary colour palette

Fig 5 -Final 2026 F/W colour palettes of data with GRU and MLP architectures

Fig 6 -Final 2026 F/W colour palettes of data with GRU and MLP architectures

To evaluate prediction accuracy, the palettes generated by the GRU and MLP architectures are compared against the actual colour values using the Delta E metric, which quantifies perceptual colour difference. Lower values indicate a good similarity or agreement with the ground truth. The comparative results are summarized in (Table 1) for GRU model and (Table 2) for MLP model where the L,a,b coordinates of the actual 2026 colours are compared against the L,a,b coordinates of the predicted values of the GRU and MLP architectures are shown.

(ΔE)

ΔE

4. Conclusion

This research offers a comprehensive analysis of Artificial Intelligence techniques for leather fashion colours forecasting through comparison of GRU, and MLP models, we have demonstrated the capabilities of these models in

ΔE

Table 1 – Delta E difference between the actual and

the predicted L,a,b coordinates – GRU Model

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forecasting the future trending colours in leather. The GRU model stands out for its accuracy and efficiency, as evidenced by the Delta E difference values with respect to the actual colours. The lowest delta E difference between the actual and the predicted colour in GRU model is 3.51. In spite of MLP's simple memoryless architecture, it outperforms GRU in some cases of input due to less variance in the input data. The lowest delta E difference recorded between the actual and the predicted colour in MLP model is 3.79. This research work aims to serve as a guide to be aware of the future leather colours. The future work in this field should aim to identify a relationship between the global colour trends and their inclusiveness indigenously, and also to predict the leather patterns so as to visualize the colours on the leather pattern.

Table 2 – Delta E difference between the actual and

the predicted L,a,b coordinates – MLP Model

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