# Leveraging Multiple Relations For Fashion Trend Forecasting Based On Social Media

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**Abstract**
Fashion trend forecasting is of great research significance in providing useful suggestions for both fashion companies and fashion lovers. Although various studies have been devoted to tackling this challenging task, they only studied limited fashion elements with highly seasonal or simple patterns, which could hardly reveal the real complex fashion trends. Moreover, the mainstream solutions for this task are still statistical-based and solely focus on time-series data modelling, which limit the forecast accuracy. Towards insightful fashion trend forecasting, previous work proposed to analyse more fine-grained fashion elements which can informatively reveal fashion trends. Specifically, it focused on detailed fashion element trend forecasting for specific user groups based on social media data. We tend to realize the design to improvise the different fashion trends, with LSTM model indicating the overall dataset from the Kaggle website with different user reviews. We improvise different features of Fashion model with indicating the different features of process with an approach is proposed to predict the future of fashion styles in different price ranges based on raw data and customer transaction data. We measure the popularity of fashion products based on statistics of past customer transactions, and predict the future trend of fashion styles in different price ranges based on consumer transactions. Finally, we compare with different machine and deep learning algorithms with its performance metrics.

**Keywords:** Forecasting, Timeseries, fashion analysis ,LSTM

## INTRODUCTION

Fashion trend forecasting plays a crucial role in the dynamic and ever-changing world of fashion. With the advent of social media, there has been a wealth of user-generated content that provides valuable insights into emerging fashion trends. Leveraging multiple relations within social media data has become an innovative approach to enhance the accuracy and effectiveness of fashion trend forecasting. In this context, "Leveraging Multiple Relations for Fashion Trend Forecasting Based on Social Media" refers to a cutting-edge methodology that harnesses the power of social media platforms to predict upcoming fashion trends. By considering various relationships and connections among users, fashion brands, influencers, and consumers, this approach aims to capture the complex dynamics and interactions that shape the fashion landscape.

The traditional methods of trend forecasting, such as surveys, fashion shows, and expert opinions, often suffer from limitations such as time delays, subjective biases, and incomplete coverage. However, social media platforms offer a vast amount of real-time data, including user-generated content, hashtags, likes, comments, and shares. These data points reflect the preferences, aspirations, and behaviors of individuals within the fashion community. By analyzing the interconnectedness between users, fashion brands, influencers, and consumers, fashion trend forecasting based on social media can identify patterns, spot emerging trends, and predict their future trajectories. This methodology employs advanced data mining techniques, natural language processing, network analysis, and machine learning algorithms to extract valuable insights from the vast pool of social media data.

The key advantage of leveraging multiple relations lies in its ability to capture the holistic nature of fashion trends. It considers not only the opinions of influencers and fashion brands but also the sentiments and interactions of individual consumers. By examining the relationships between these entities and how they influence each other, this approach can provide a more comprehensive and accurate prediction of fashion trends. "Leveraging Multiple Relations for Fashion Trend Forecasting Based on Social Media" represents an innovative and data-driven approach to predict fashion trends. By harnessing the power of social media data and considering the various relationships within the fashion community, this methodology offers a more dynamic, real-time, and inclusive way to stay ahead in the fast-paced world of fashion.

## LITERATURE SURVEY

Fashion trends come and go; meanwhile a society's values are established and evolving characteristic to their beliefs and culture. Fashion is just not an ambitious projected image of a reinterpreted good old value to fulfill some function or agenda alike but rather a evocative and refreshing concept worthy enough to be portrayed for society's appreciation that makes us even more instinctive. In the society, the individual's appearance is the ticket to transmit non verbal communication signals such as possible cues about his / her social stature, values and lifestyle. Fashion communication has under gone a 360 degree shift in its communicable aspects staring from projecting a basic image of how we look like and how we feel like to expressing our emotional experiences through interactive implements in the dress.

The success of the fashion trend lies in the way the society interprets the fashion trend and judges it. Hence the impact is measured by the barometer of social acceptance which in turn is driven by the several motivational forces that underline the people's values and behavioral traits. Today's consumer culture is driven by aspirationalism that diminishes the gap between the rich and economically volatile sections when it comes to accepting and adopting a trend. A classical example is, a consumer in China saves her three months salary to purchase a LVMH hand bag. Further It does not stop here as the people's cash liquidity is extended by the easy provision of personal loans facilitated by both private and nationalized banks alike. This is even extended by few Brands' initiatives to offer fashion products on a credit basis with easy monthly part payment options.

Today's youth ( 15 to 20 years) given their predictable audacity, the tendency to shop, venture out, try, experiment is high, it is they who decide the life time of a fashion trend. In a globalized world well connected by web technologies, geographical distance is no more a constraint to reach and witness the experience. The lines between buying behaviors are no more significant among young people ( youth) indeed blurring out as the common urge is get hooked on to social networks, interact across a wide section of people of with shared interests and get appreciated. In fact even companies hiring potential job seekers are verifying their social networks and appraising them. In this context, the very idea of consumerist model of Top to down approach is hardly relevant. (Douglas & Isherwood, 1996; McCracken, 1990) theories of consumption describe a more complex picture in which fashion does more than signal social position. Rather populist models and trickle across theories help to explain the phenomenon better. A classical example is the prevalence of their attitude and lifestyle to decide about product purchase rather than merely following the cultural stars and people in lime light or the rich and wealthy people. Today's world is driven by knowledge and experience providing chance for every individual to experience and appreciates a moment which is no way decided by their monetary status. And the converse is also true that the rich are not the only ones superior in appreciating a taste or value. And knowledge being a common platform where rich and economically vulnerable alike compete on equal terms. In fact the new line is between knowledge ignorant people and people with well equipped knowledge.

(Holt 1997a) defines lifestyle as collective pattern of consumption patterns based on shared cultural frameworks that exist in social system. A recent analysis on the consumer consumption behavior by Chaudhuri and Majumdar (2006) only bears more evidence to this phenomenon.

The phenomenon of fashion can be distinguished into elite fashion ( haute couture) and everyday fashion rather than just restricting ourselves to the concept of European or western high fashion. (Malcom barnard 1996, 2008) Everyday Fashion is an interactive process through which the aspiring individuals of the society consciously project their bodily self in a distinctive manner in the form of clothing style. it is unlike the traditional capitalist fashion system where the so called elite or rich decide the course of fashion tastes and fashion gets disseminated from the top to bottom sections of the society. This distinctive manner of style is equally drawn from the fashion trends percolated through contemporary life, style conventions, fashion code concepts developed by the designers & forecasting service providers alike and street style fashion, Appreciation of aesthetic experiences, ethnographic accounts witnessed in the social vicinity of a local population. (Malcolm barnard 1996, 2008) Relating to the beliefs and attitudes of the peers or social group these individuals belong to the Endeavour to draw a fine line between the existing patterns of style and their appearance by dressing in a trendy manner.

## PROPOSED CONFIGURATION

Karl Lagerfeld 1 used to say that the essence of fashion is changeability. Fashion trend forecasting, aiming to master such change, is therefore of great significance in fashion industry. It enables fashion companies to develop products and establish marketing strategies more wisely. It also helps fashion consumers make better choices. Traditionally, to predict fashion trends, the staffs of forecasting companies travel across the world to observe the art, music, and other cultural factors that may influence fashion industry. Also, the staffs collect information of consumers' ways of living, thinking, and behaving . However, the existing solutions mainly rely on subjective inferences of these forecasters, which may be less reliable and have large variations. In the recent decade, technological innovations such as Internet has accelerated the rate of fashion change, which makes fashion trend forecasting even more difficult. On the other hand, the advent of digital age has facilitated the accumulation of huge amounts of fashion-related data, which provides an alternative data-driven way of addressing the fashion trend forecasting task . Our design aims to mine useful fashion information from big

historical data and predict the possible development of fashion for the future There are two main research challenges for this task:
1) What kind of data should be used and analyzed in order to make meaningful and relevant fashion trend forecasting?
2) How to effectively model relevant data to make accurate predictions?

For the first challenge, the source data should contain abundant time series fashion information, and should also be of considerable scale to cover a rather long time period in order to reflect the evolution of fashion over time. Compared to e-commence or fashion show , social media is a more appropriate data source because it sensitively and extensively records the fashion development with massive uploaded fashion-related images and comments everyday from multiple sources of end users, fashion bloggers and brands, etc. Besides, rich information for both users and fashion items can be extracted from the images, meta data and other source data by the well-developed computer vision or other machine learning techniques. Although there exists datasets based on social media , they contain very limited fashion elements and are far from enough for forecasting meaningful and applicable fashion trends. Also, the information of users (such as age, gender or living location) that actually convey most fashion-related data is essential in fashion trend observation. Such user information, however, is neglected in existing datasets. Considering the limitations of existing datasets, in this paper, we build a new dataset with extensive fine-grained fashion elements, including category, attribute and style. It also covers a longer time period with richer user information.

For the second challenge, in order to make accurate data-driven fashion trend forecasting, the underlying patterns in the time series data need to be effectively captured. Though traditional models such as statistical models or matrix factorization have been effectively applied to model simple time series data , they fall short of ability to make sound predictions for more complicated fashion trends. Recent advances of deep learning have provided great solutions for many tasks . In particular, the recurrent neural networks (RNN) have demonstrated its superiority in modeling time series data and addressing relevant problems . However, such approaches have not been employed in the area of fashion trend analysis yet. On the other hand, most existing works predict the trend of each fashion element independently. However, according to common sense, fashion elements are not independent but well-correlated with each other in various ways. For example as shown in Figure 1, the trend of sweater shows similar pattern with that of turtle neck, but nearly opposite with that of dress. If we try to predict the trend of sweater, we can apply the prediction results on both the turtle neck and dress to refine the prediction of sweater based on their observed correlations. Furthermore, in fashion domain, there naturally exist taxonomic relations between elements, e.g., the affiliation relations between sweater and all its affiliation attributes as shown in Figure 1. Such taxonomic relations would result in relations among fashion trend patterns, which we should take advantage of in fashion trend modeling. In short, these types of prior domain knowledge describing the relations among fashion trends are non-trivial to model but helpful. Driven by the above motivations, proposed work presents an approach named L-CNN for forecasting fashion trends of people in various groups.

Activity Diagrams describe how activities are coordinated to provide a service which can be at different levels of abstraction. Typically, an event needs to be achieved by some operations, particularly where the operation is intended to achieve a number of different things that require coordination, or how the events in a single use case relate to one another, in particular, use cases where activities may overlap and require coordination. It is also suitable for modeling how a collection of use cases coordinate to represent business workflows.

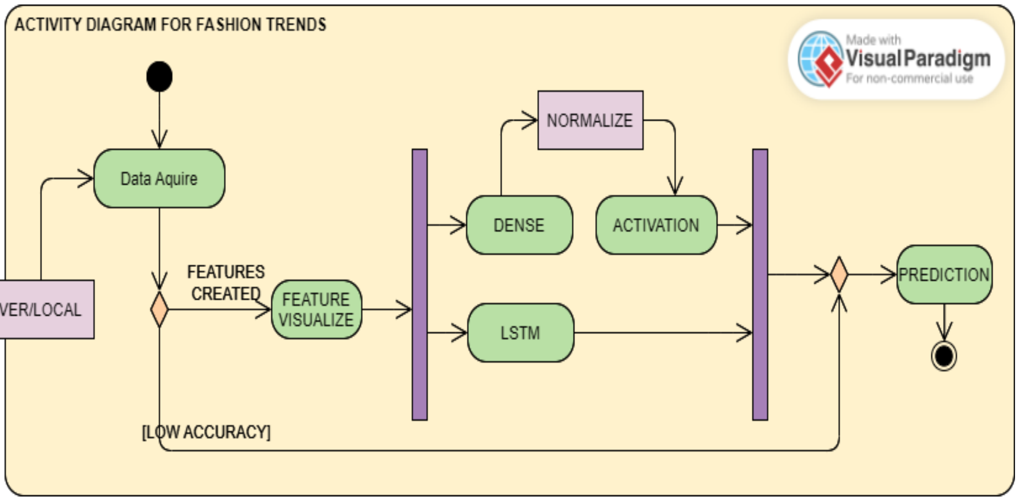


**Fig 1** Activity diagram

The proposed approach effectively models the time series data of fashion elements with rather complex patterns by using the Long-Short Term Memory (LSTM) encoder-decoder framework. More importantly, it incorporates two types of knowledge: internal and external knowledge. Specifically, for internal knowledge, it leverages the similarity relations of time series within dataset and introduces a triplet regularization loss based on pattern similarities.

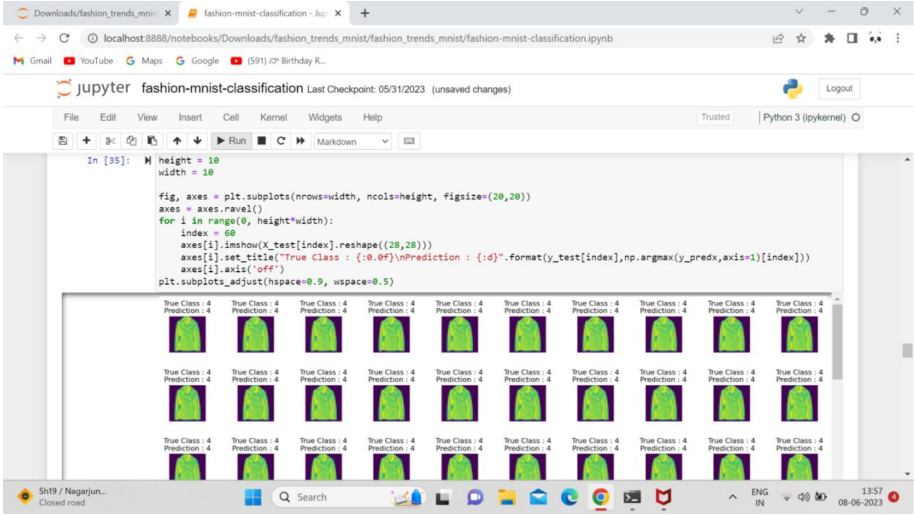


**Fig 2** picture of trouser when index is 60

For external knowledge, it takes advantage of the affiliation relations of fashion elements within the taxonomy, and incorporates them by updating the embedding of fashion elements via message passing. The proposed CNN model incorporates both the time series information of single fashion element and the connectivity between this element and all related ones. We also exploit the user information for better modeling the different fashion trends for different groups of users by applying the semantic group representation.

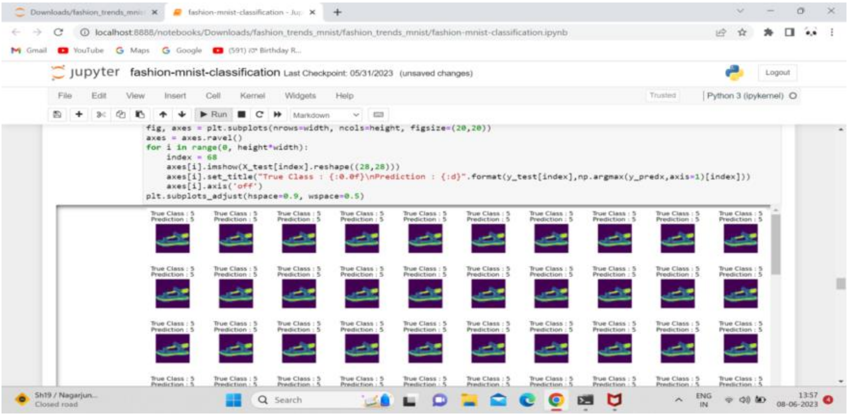

**Fig 3** Picture of shoes when index is 68

Time Series Forecasting Fashion trend forecasting is also closely related to the time series forecasting problem which aims to predict the future based on the historical observations. Statistic models are classic solutions for time series forecasting problems, including the most representative autoregrassive (AR), moving averages (MA), improved autoregressive integrated moving average (ARIMA) , and others . These models were found to be quite effective for forecasting structural data with high seasonality or simple trend.

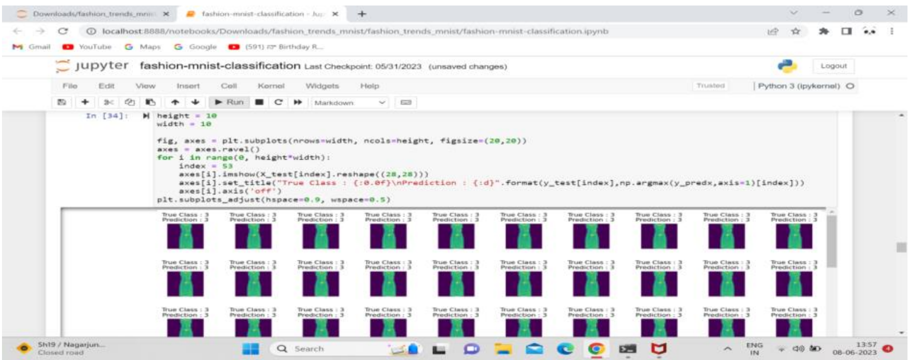

**Fig 4** Picture of frock when index is 53

However, the real-life times-series signals are usually highly volatile and very difficult to model by these traditional methods. Recently, with the success of deep neural networks in a wide range of tasks, RNN, especially its variant LSTM

, has shown its superiority in modeling sequential data and achieved superior performance in various applications of NLP, speech recognition, and also time series forecasting .

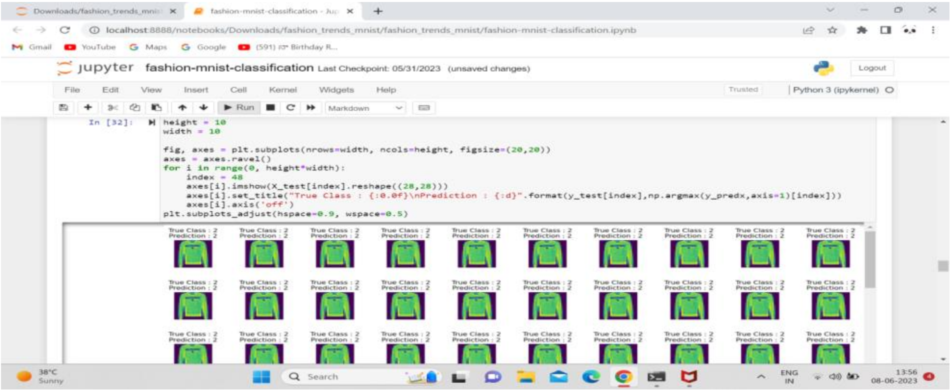


**Fig 5** Picture of when hudi index is 48

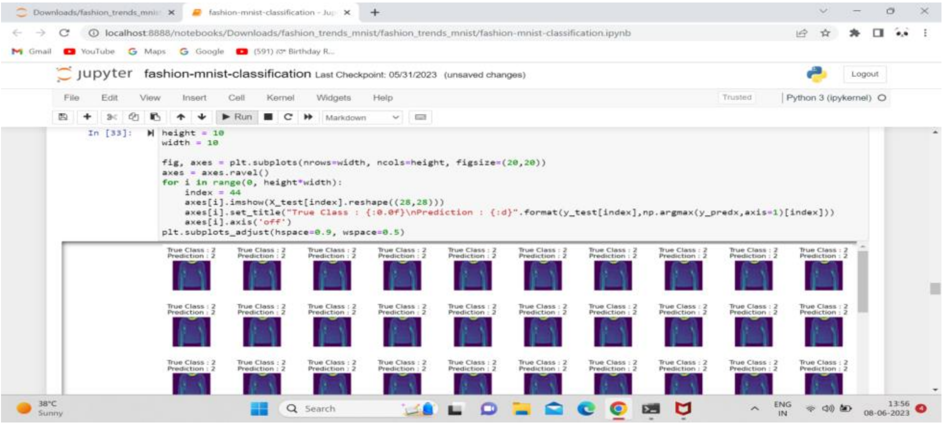


**Fig 6** Picture of t-shirt when index is 44

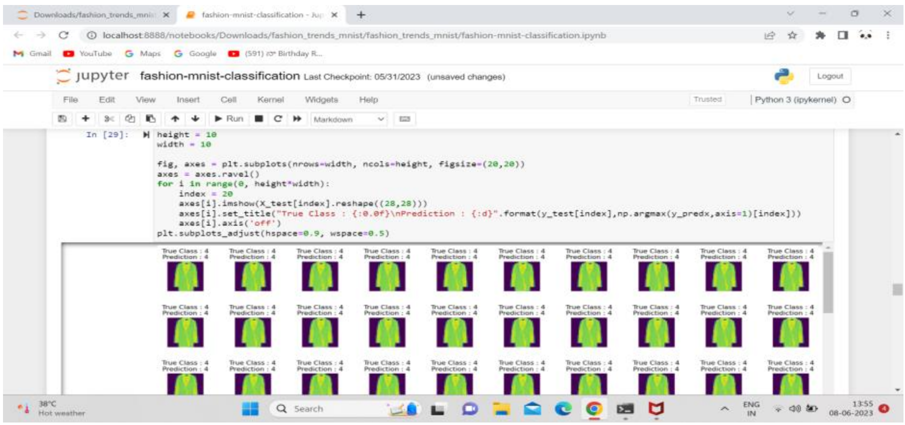


**Fig 7** Picture of kurti when index is 20

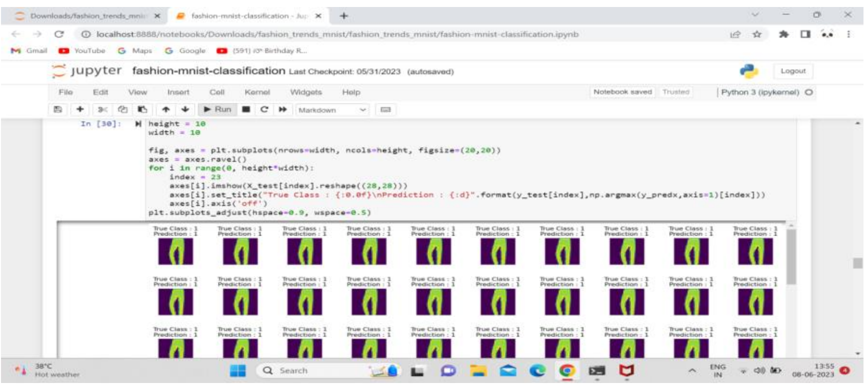


**Fig 8** Picture of jeans when index is 23

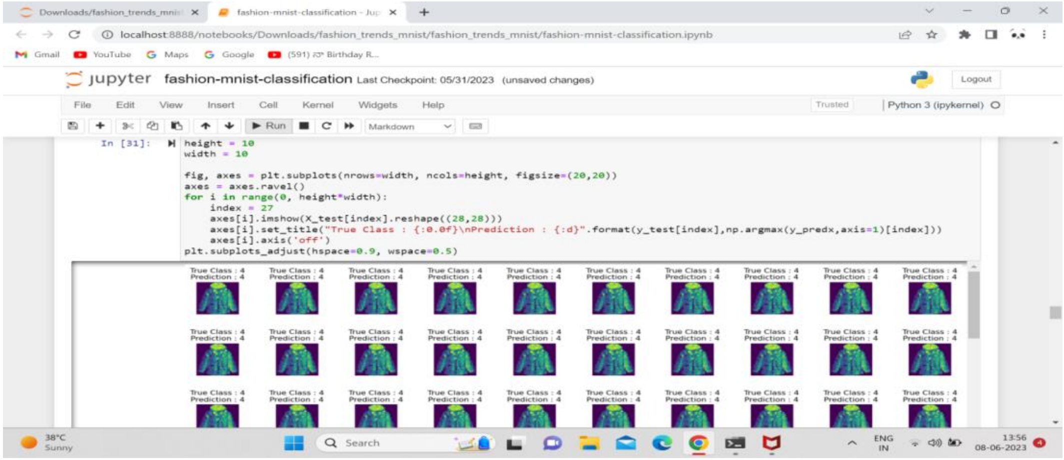

**Fig 9** Picture of shirt when index is 27

Since fashion trend forecasting is a rather domain-specific task, leveraging abundant fashion knowledge in the forecasting task is a viable approach. Actually, exploiting domain knowledge, or external knowledge, to enhance the performance of deep learning models has achieved promising results lately in many tasks . Specifically, in time series forecasting problems like the stock price prediction, Feng et al. found that incorporating domain knowledge of stocks (e.g., companies within the same industry sector) can effectively help stock price forecasting. Despite of many successful applications, domain knowledge has not been well exploited in fashion trend forecasting.

## CONCLUSION

we address the problem of distinguishing clothing elements in fashion photographs using a L-CNN. This is accomplished using the fashion MNIST dataset, which contains many images, together with L-CNN and ANN algorithms for accurate and effective image classification. Image recognition is becoming increasingly crucial as deep learning algorithms progress. CNN recognition is commonly used when it comes to fashion-related applications, such as garment classification, retrieval, and computerised clothing labelling. In this study, we employ L-CNN architecture on the Fashion MNIST dataset. We would like to compare this with different datasets. Fashion MNIST is a dataset having low-resolution images. We would like to try these high-resolution images in the future, and we also plan to put L-CNN architecture to the test on a dataset of real-life apparel pictures that we amassed ourselves.

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