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Social Media Accessed By Several Members To Estimate Fashion Trends

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A B S T R A C T

Forecasting fashion trends has significant research implications because it can offer helpful advice to both fashion businesses and fashion enthusiasts. Despite the fact that numerous studies have been committed to handling this difficult issue, they only looked at a small number of fashion items with primarily seasonal or simple patterns, which scarcely revealed the true complicated fashion trends. Additionally, the commonly used approaches for completing this task are still focused on statistics and only concentrate on time-series data modelling, which restricts the forecast's accuracy. Previous research suggested analysing more minute fashion components that could usefully identify fashion trends in order to produce effective fashion trend forecasting. In particular, it concentrated on certain user groups' comprehensive fashion element trend forecasts based on social media data. With LSTM model indicating the whole dataset from the Kaggle website and various user ratings, we estimate the popularity of fashion products based on photos. We have a tendency to realise the design to innovate the various fashion trends. Finally, we compare the performance metrics of the CNN and LSTM algorithms.

Keywords: Fashion, Trends, Social Media

1. INTRODUCTION

Fashion has many diverse definitions, and its use is somewhat ambiguous. The term "fashion" denotes both similarity and difference, as in "the new fashions of the season" or "the fashions of the 1960s," which both suggest a general consistency. Fashion can represent the most recent trends, but it can also frequently allude to styles from the past, causing such styles to come back into style. While a relatively exclusive, well-respected, and frequently wealthy aesthetic elite can define what is fashionable by creating an exclusive look, such as fashion houses and haute couturiers, this "look" is frequently created by drawing references from subcultures and social groups that are not considered elite and are therefore disqualified from defining what is fashionable themselves.

Fashion is a unique and industry-supported expression historically connected to the fashion season and collections, as opposed to trends, which frequently connote an odd aesthetic expression, frequently lasting less than a season, and being recognisable by visual extremes.[6] A long-lasting form of expression, style is frequently linked to social markers, symbolism, class, and culture (such as Baroque and Rococo), as well as to cultural movements. Sociologist Pierre Bourdieu claimed that fashion signifies "the latest difference."[7]

Even though the terms "fashion," "clothing," and "costume" are sometimes used interchangeably, they are not the same thing. Costume now refers to fancy dress or masquerade wear; clothing denotes the material and the technical garment, devoid of any social significance or ties. Contrarily, fashion describes the social and chronological framework that shapes and "activates" clothing as a social cue in a particular period and setting. Giorgio Agamben, a philosopher, relates clothes to the quantitative concept of chronos, the personification of chronological or sequential time, and fashion to the qualitative Ancient Greek concept of kairos, which means "the right, critical, or opportune moment."[8]

Although several high-end brands may use the word haute couture, only those who are members of the Chambre Syndicale de la Haute Couture[9] in Paris are authorised to use it.[6] Haute couture is more aspired-to; it is frequently only worn by the wealthy and is inspired by art and culture.

Fashion is an additional form of art that enables individuals to express their distinct aesthetic preferences.[10] Different fashion designers take inspiration from external stimuli and incorporate it into their designs. For instance, whereas Gucci's "stained green" jeans[11] may appear to have a grass stain, others may perceive them to be pure, fresh, and summery.[1]

Fashion is distinctive, self-fulfilling, and may play a significant role in a person's identity. Similar to art, a person's fashion choices should be an expression of their own tastes rather than necessarily being accepted by others.[10] The way someone dresses serves as a "societal formation that always combines two opposite principlesIn addition to being a safe and socially acceptable technique to set oneself apart from others, it also meets a person's desire for social adaptation and imitation.[12] Sociologist Georg Simmel[13] thought that fashion "helped overcome the distance between an individual and his society" whereas philosopher Immanuel Kant thought that fashion "has nothing to do with genuine judgements of taste" and is instead "a case of unreflected and 'blind' imitation"[12]

2. LITERATURE SURVEY

CNN Model for Image Classification on MNIST and Fashion-MNIST Dataset

AUTHORS: Shivam S. Kadam, A. Adamuthe, Ashwini Patil

They presented application of convolutional neural network for image classification problem. MNIST and Fashion-MNIST datasets used to test the performance of CNN model. Paper presents five different architectures with varying convolutional layers, filter size and fully connected layers. Experiments conducted with varying hyper-parameters namely activation function, optimizer, learning rate, dropout rate and batch size. Results show that selection of activation function, optimizer and dropout rate has impact on accuracy of results. All architectures give accuracy more than 99% for MNIST dataset. Fashion-MNIST dataset is complex than MNIST. For Fashion-MNIST dataset architecture 3 gives better results. Review of obtained results and from literature shows that CNN is suitable for image classification for MNIST and Fashion-MNIST dataset.

Hierarchical Convolutional Neural Networks for Fashion Image Classification

AUTHORS: Yian Seo, Kyung shik Shin

Deep learning can be applied in various business fields for better performance. Especially, fashion-related businesses have started to apply deep learning techniques on their e-commerce such as apparel recognition, apparel search and retrieval engine, and automatic product recommendation. The most important backbone of these applications is the image classification task. However, apparel classification can be difficult due to its various apparel properties, and complexity in the depth of categorization. In other words, multi-class apparel classification can be hard and ambiguous to separate among similar classes. Here, we find the need of image classification reflecting hierarchical structure of apparel categories. In most of the previous studies, hierarchy has not been considered in image classification when using Convolutional Neural Networks (CNN), and not even in fashion image classification using other methodologies. In this paper, we propose to apply Hierarchical Convolutional Neural Networks (H–CNN) on apparel classification. This study has contribution in that this is the first trial to apply hierarchical classification of apparel using CNN and has significance in that the proposed model is a knowledge embedded classifier outputting hierarchical information. We implement H–CNN using VGGNet on Fashion-MNIST dataset. Results have shown that when using H–CNN model, the loss gets decreased and the accuracy gets improved than the base model without hierarchical structure. We conclude that H–CNN brings better performance in classifying apparel.

Classification of Fashion Article Images Using Convolutional Neural Networks

AUTHORS: Shobhit Bhatnagar, Deepanway Ghosal, M Kolekar

A state-of-the-art model for classification of fashion article images is proposed. Convolutional neural network based deep learning architecture to classify images in the Fashion-MNIST dataset is trained. Three different convolutional neural network architectures are proposed and used batch normalization and residual skip connections for ease and acceleration of learning process. This model shows impressive results on the benchmark dataset of Fashion-MNIST.

A Novel Clothing Attribute Representation Network-Based Self-Attention Mechanism

AUTHORS: Y. Chun, C. Wang, and M. He

As highly increasing of on-line fashions retail industry, automatic recognition and representation of clothing items have huge potentials. With the help of deep learning methods, many clothing attribute representation models have been proposed. However, these models are mainly suitable for coarse-grained classification which are not suitable for clothing attribute representation. To address such a problem, in this article, we propose a novel network structure named SAC, which is a combination of CNNs and Self-attention mechanism and can represent clothing attributes more fine-grained. Besides, we use Grad-CAM to visualize which part of the clothing attributes is more concerned by customers. Finally, a new labeled clothing dataset is introduced in this article, which is expected to be helpful to the researchers who are working in fashion domains for image representation.

3. PROPOSED SYSTEM

The Long-Short Term Memory (LSTM) encoder-decoder framework is used to model the time series data of fashion items with relatively complex patterns in the proposed approach. More significantly, it combines internal and exterior information, two different types of knowledge. For internal knowledge, it specifically makes use of the time series similarity relations within the dataset and provides a triplet regularization loss based on pattern similarity. By updating the embedding of fashion elements via message passing, it adds external knowledge by utilizing the affiliation relations of fashion elements within the taxonomy. The suggested CNN model takes into account both the time series data of a single fashion component and the relationships between that component and all others that are connected. By using the semantic group representation, we also make better use of the user data to model various fashion trends for various user groups.

Long-Short Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a kind of Recurrent Neural Network (RNN) that may be characterized as RNNs that are trained to learn and adapt for long-term dependencies The single trait it naturally possesses is the ability to remember and recall prior information for a longer period of time. The field of time series prediction frequently employs LSTMs due to its capacity to store memory or previous inputs. This is because they were designed to retain information over a long length of time. Its similarity to a chain is due to the fact that both systems include four interacting levels that interact with one another in different ways. They may be used in applications involving time series prediction in addition to the production of pharmaceuticals, the development of voice recognizers, and the creation of musical loops.

The LSTM's operations happen in a logical sequence. To start, people frequently forget tiny details that they learned in the condition before that one. Then, they choose how to update specific values of the cell state before producing specific features of the cell state as output. You can see a flowchart of how they work below.

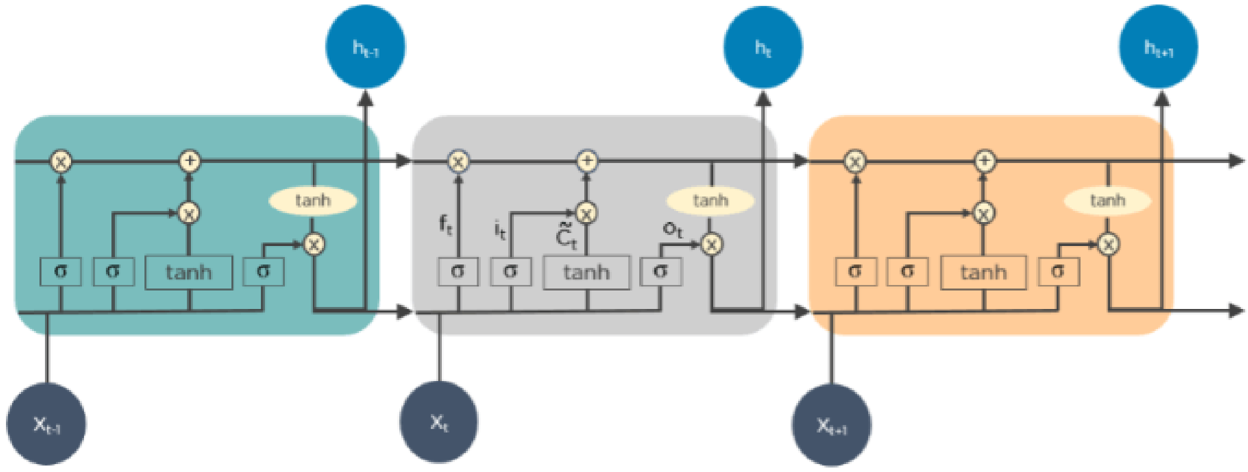

Figure: Representing the LSTM structure with Tanh Activation layer

Convolutional Neural Network (CNN)

CNNs, often referred to as ConvNets and more frequently known by their acronyms, are employed specifically for object recognition and image processing. They generally consist of several layers. It was created by Yann LeCun in 1998, and its original name was LeNet. It was created at that time to recognise zip code characters and numeric characters. Common uses for CNNs include the identification of satellite image data, processing of medical pictures, series forecasting, and anomaly detection.

Data is processed by CNNs by first passing it through a number of layers, after which properties that show convolutional processes are extracted. The Convolutional Layer, which corrects the feature map, is composed of Rectified Linear Units (ReLU). These feature maps are adjusted in the Pooling layer before being sent into the following layer. Pooling is a sampling technique that, in the majority of circumstances, produces a down sampled data set and also helps to reduce the feature map's dimensions. In the end, the output is a two-dimensional array of flattened linear vectors that are single, long, continuous, and linear in direction. The fully connected layer, which comes after, is in charge of creating the flattened matrix or two-dimensional array that the pooling layer uses as input. This layer is also in charge of classifying and categorizing the image.

A typical Deep Learning neural network architecture in computer vision is the **Convolutional Neural Network (CNN).** A computer can comprehend and analyse visual data or images thanks to the field of artificial intelligence known as computer vision.

Artificial neural networks do incredibly well in machine learning. In many datasets, including those with images, audio, and text, neural networks are used. Different forms of neural networks are employed for various tasks. For example, to predict the order of words, recurrent neural networks—more specifically, an LSTM—are used. Similarly, to classify images, convolution neural networks are employed. We're going to create the fundamental building element for CNN in this paper.

In a regular Neural Network there are three types of layers:

1. **Input Layers:** It's the layer in which we give input to our model. The number of neurons in this layer is equal to the total number of features in our data (number of pixels in the case of an image).
2. **Hidden Layer:** The input from the Input layer is then feed into the hidden layer. There can be many hidden layers depending upon our model and data size. Each hidden layer can have different numbers of neurons which are generally greater than the number of features. The output from each layer is computed by matrix multiplication of output of the previous layer with learnable weights of that layer and then by the addition of learnable biases followed by activation function which makes the network nonlinear.

3. **Output Layer:** The output from the hidden layer is then fed into a logistic function like sigmoid or softmax which converts the output of each class into the probability score of each class.

In the following stage, known as Feedforward, the model is supplied with input, and each layer's output is obtained. We then calculate the error using an error function; some popular error functions are cross-entropy, square loss error, etc. The network's efficiency is gauged by the error function. After that, we calculate the derivatives and backpropagate into the model. Backpropagation is the process that is utilised to reduce loss in general.

Artificial neural networks (ANN) have evolved into Convolutional Neural Networks (CNN), which are mostly used to extract features from datasets with grid-like matrixes. Examples of visual datasets where data patterns play a significant role are photographs and movies.

Convolutional Neural Network consists of multiple layers like the input layer, Convolutional layer, Pooling layer, and fully connected layers.

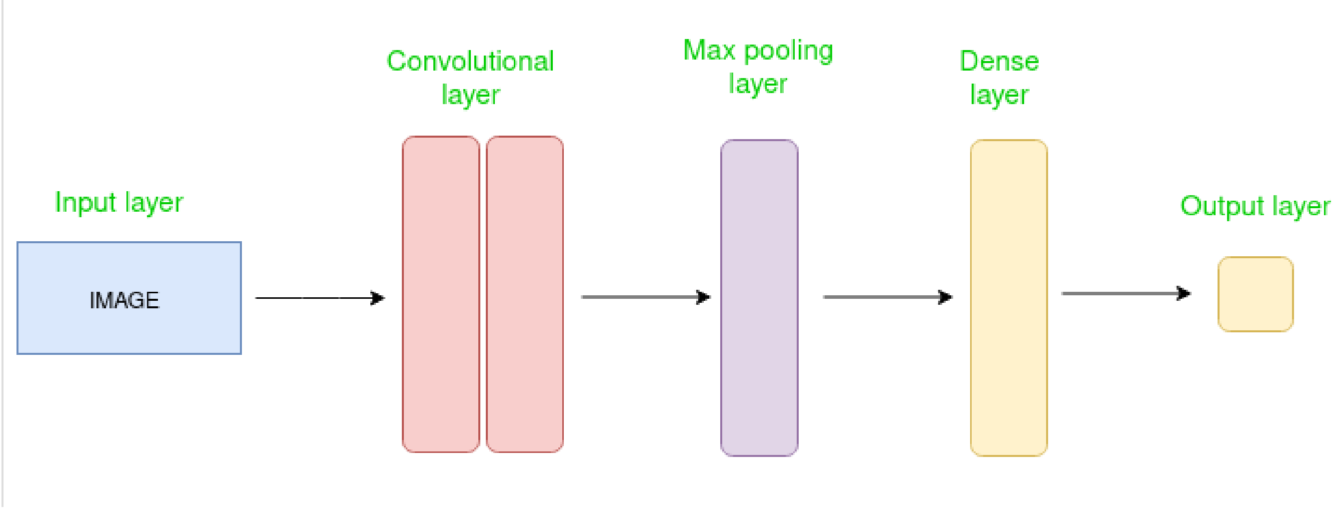

Figure: CNN Architecture

BLOCK DIAGRAM

The data is initially collected (which includes data on various fashion trends) and pre-processed. Trend characteristics are retrieved from the chosen data, normalised (converting the raw data to numerical form), and then applied to the deep learning model (LSTM & CNN). Now, these extracted features are applied to the LSTM, Dense, and CNN layers and provided to the classification model for the purposes of image recognition, processing pixel data, and forecasting fashion trends. The data is now split into training features and testing features in an 80:20 ratio, after which the model is fitted and assembled. The loss and accuracy, which are divided into validation loss and accuracy and training loss and accuracy, will be described in detail. It produces the product of forecasting fashion trends by foreseeing test cases.

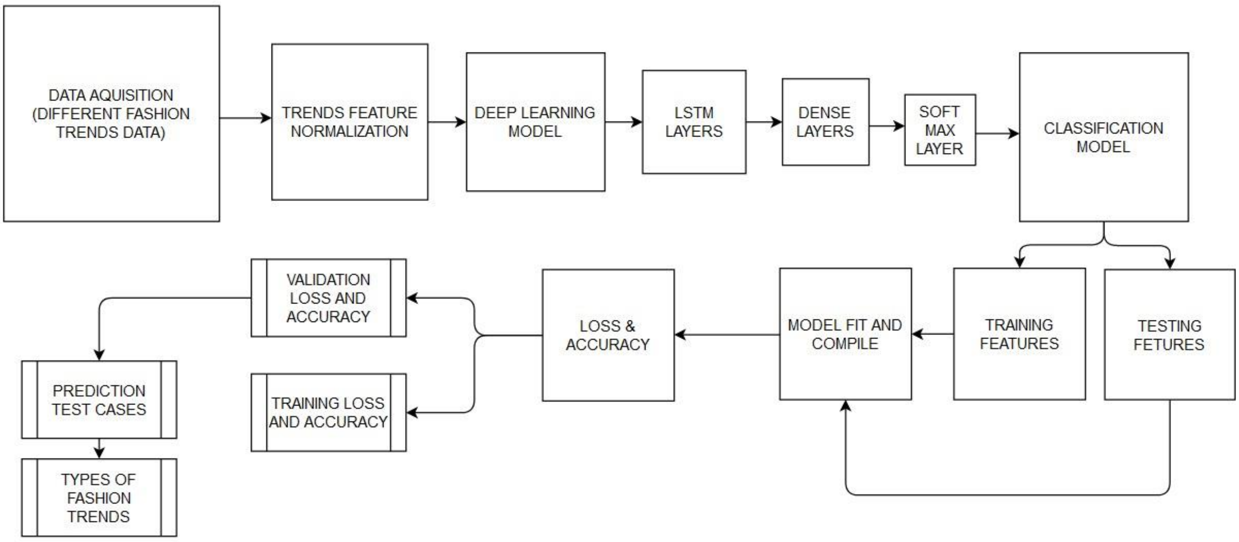

Figure: Block Diagram of the System

4. CONCLUSION

Using an L-CNN, we tackle the issue of identifying apparel components in fashion pictures. The fashion MNIST dataset, which comprises a large number of photos, along with LSTM and CNN algorithms for precise and efficient image categorization, are used to do this. With the development of deep learning algorithms, image recognition is becoming more and more important.. When it comes to fashion-related applications like garment classification, retrieval, and computerized clothing tagging, CNN recognition is frequently used. On the Fashion MNIST dataset, we use L-CNN architecture in this study. We want to contrast this with various datasets. A dataset called Fashion MNIST contains photos with low resolution. In addition to testing L-CNN architecture on a dataset of real-world garment photographs that we acquired ourselves, we hope to try these high-resolution images in the future.5.

5. FUTURE ENHANCEMENTS

More study is required in order to try this with high-resolution photos in future work. On a set of our own collection of real-world clothes images, we also intend to test the L-CNN architecture. With more research, it will be possible to incorporate new features in the future to enhance the model's accuracy and reliability. The best fashion for all age groups can even be suggested by adding a camera (which will automatically capture photographs of the outfits and offer commonalities) and a fashion suggestion module.

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