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APPLICATION OF FASHION ELEMENT TREND PREDICTION MODEL INTEGRATING AM AND EFFICIENTNET-B7 MODELS IN ART DESIGN

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Abstract. With the rapid development of the fashion industry and the increasing diversification of consumer needs, accurately predicting the fashion trends of clothing elements has become an urgent problem in the field of art design. In order to solve these problems, this paper uses deep learning technology for fashion trend prediction and optimization of prediction models. Firstly, the EfficientNet-b7 model is constructed as an attribute predictor to accurately extract the attributes of clothing image elements. Then, based on user information, popular elements are grouped and counted to solve the problem of different populations having different opinions on popular trends. The prediction model is constructed based on the bidirectional long short-term memory network encoder decoder framework, which trains trend information as a whole and utilizes element coexistence relationships to assist in trend prediction. Meanwhile, the study uses random sampling method for clothing original adoption, and the experimental results show that the model considering coexistence relationship performs the best in terms of mean absolute error and mean absolute percentage error, which are 0.0132 and 14.68%, respectively. In addition, the model that introduces attention mechanism based on trend similarity has improved by 5.09% and 4.54% on two indicators compared to the latest model. The experimental results indicate that coexistence relationships can help improve the performance of prediction models. The attention mechanism based on trend similarity can further improve model performance by similarity comparison between historical information and changing trend, and selecting similar historical information as an important influencing factor for future trends.

Key words: Clothing elements; Trend prediction; EfficientNet; BiLSTM; Attention mechanism

1. Introduction. In the context of the rapid development of the clothing industry, accurately grasping clothing fashion elements trend is crucial for improving the competitiveness of enterprises and occupying the market. However, traditional experiential fashion trend prediction methods gradually show limitations in the face of large amounts of data and changing market environments [1-3]. As Internet and big data technology develop, data-driven prediction methods have gradually become a new way to achieve objective, fast, and accurate predictions . Kaur P et al. used machine learning algorithms for effective identification and monitoring of pests and diseases such as grapes [4]. Based on the predicted results of fashion trends, art designers can more accurately grasp fashion trends and provide strong reference for their own design . Burgan H İ and other scholars utilized statistical methods of data to monitor relevant physical and inorganic chemical parameters [5]. The model can extract hidden patterns and interaction patterns between elements in fashion trends from massive data, helping designers better present and convey the concept of fashion art . Mahaveerakannan R et al. Automated prediction and detection of forest fires using artificial intelligence techniques [6]. Meanwhile, predictive models are a powerful competitive tool for clothing companies. By quickly, objectively, and accurately predicting fashion trends, enterprises can adjust their production and sales strategies in a timely manner, reduce inventory risks, increase sales volume, and customer satisfaction [7-8]. Therefore, the study utilizes deep learning technology to construct an attribute predictor based on the EfficientNet-b7 model, and groups and statistics clothing popular elements based on user information. The prediction model is based on the Bidirectional Long Short Term Memory Network (BiLSTM) encoder decoder framework, which trains elements trend as a whole and utilizes the coexistence relationship between elements to assist in trend prediction. The novelty of the Fashion Trend Prediction Model of Clothing Elements Integrating AM and EfficientNet-b7 Models in Fine Art Design is that it combines two different neural network models to analyze and mine the trend of fashion elements through the AM model, and then use the EfficientNet-b7 model to identify and predict the clothing elements,

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which can help the fine art designers to more accurately The EfficientNet-b7 model is then used to recognize and predict clothing elements, thus helping art designers to more accurately grasp fashion trends and design more competitive works in the market. Compared with previous techniques, this model is novel in that it utilizes two different neural network models, giving full play to their respective advantages and making the prediction results more accurate and reliable. The research aims to provide accurate prediction results for designers, assist in design creation, and play a crucial role in the operational decision-making of enterprises. The first section of the article provides an overview of relevant research results at home and abroad, indicating the necessity and feasibility of the research. Then, the second section provides a detailed introduction to the methods proposed in the study and their improvements. The third section of the article introduces the experiments and results obtained to verify model's performance, and finally summarizes the entire study in the fourth section.

2. Related Work. Deep learning is a machine learning method that can achieve learning and analysis of large-scale data by simulating the neuronal network of the human brain through a multilayer neural network. Deep learning extracts features from data through multi-layer neural networks and gradually improves the abstraction ability of the data, thus realizing the solution and prediction of complex problems. Deep learning has made remarkable achievements in the fields of speech recognition, image recognition, and natural language processing, and has been widely used in various fields. In deep learning, trend prediction estimates the future development direction of the research object through the gradual deepening of people's understanding of objectively existing things and the continuous development of relevant research means, with the aim of selecting future behaviors. Trend prediction estimates the future development direction of the research object through the gradual deepening of people's understanding of objectively existing things and the continuous development of relevant research methods, with the aim of making choices about future behavior. Scholars and Shafiq M O proposed a stock market price trend prediction scheme that includes feature engineering customization and deep learning models. This scheme comprehensively considered the preprocessing of stock market datasets, the utilization of various feature engineering technologies, and combined customized deep learning systems for prediction, making contributions to the stock analysis research community in the financial and technical fields [9]. Xu and other scholars proposed a scientific research topic trend prediction model based on multiple LSTM and graph convolutional networks. By using multiple LSTMs to map the research topics of different publications into their respective topic spaces, and then using graph convolutional neural networks to learn the scientific impact background of each publication, it had important reference significance for researchers to understand the development of the discipline, decision-makers to make decisions, and fund allocation [10]. Scholars such as Picasso mapped the stock market prediction problem to a classification task of time series data, with technical analysis indicators and sentiment in news articles used as inputs. A powerful prediction model was obtained for high-frequency trading simulations, achieving an annualized return rate of over 80%. This project represented further steps in combining technology and basic analysis, and provided a starting point for developing new trading strategies [11]. Scholars such as Hu Y proposed a trend tracking strategy for security prediction using LSTM networks, where the training method combined particle swarm optimization algorithm with gradient descent to obtain more competitive model parameters. Firstly, three trend representation methods were defined based on stock option research, and then a fusion algorithm optimized LSTM network was used for trend tracking. From the perspective of security prediction, the trends of changes were further predicted and analyzed over different time periods [12].

With the continuous development of deep learning technology and in-depth research, new developments have been made in learning the trends and patterns of fashion fashion elements and their mutual influence. Dong et al. designed an interactive knowledge-based design recommendation system to provide product design solutions and virtual demonstrations to specific consumers. This system utilized a 3D body scanning system and sensory evaluation program to obtain anthropometric data and designers' perception of body shape, and used fuzzy technology to model and classify the relationship between body shape, fashion themes, and design factors [13]. Wu D et al. proposed a novel relationship network for clothing attribute recognition. This network utilized a backbone network to extract features from input images, and then further learned these features through two attention models. It also utilized a graphical context inference module to further enhance the features, and finally used a classifier to classify clothing attributes based on the learned representation information. This method effectively utilized the relationships between objects to improve recognition accuracy [14]. Lu et al.

developed a multi-layer non local feature fusion framework for studying clothing matching compatibility. The feature fusion model was used to merge high-level and low-level features, while non local blocks were used for global feature detection. This technology was compared with previous state-of-the-art methods in compatibility prediction tasks and its effectiveness was demonstrated through extensive experiments on existing datasets [15]. Yang and Jang S used two calculation methods, ARIMA and RNN, to predict fashion trends. Researchers predicted women's skirts, selected the best model by comparing the results, and proposed the time points of change that should be paid attention to in fashion trends. Cautious application of deep learning methods was suggested in fashion product planning to improve the applicability of trend prediction [16].

Based on relevant research both domestically and internationally, it can be found that the continuous development of technology will make the prediction results more rich and accurate. However, further improvement requires a combination of factors that affect the development of fashion trends in the clothing industry. The trend of clothing fashion elements has a certain connection with different groups of people, and different groups of people have different views on clothing fashion trends. Combining user information is a very important research direction, while continuing to combine the patterns of fashion trend elements is the focus of future research. Therefore, the study utilizes BiLSTM to make more accurate predictions.

3. Fashion Element Trend Prediction Model Based on AM Fusion EfficientNet-b7. Finding the trend patterns from historical data related to clothing and making predictions can help art designers more accurately grasp fashion trends, thereby providing strong reference for design. The research aims to improve the accuracy of fashion trend prediction, combining the coexistence relationship between fashion elements and the attention mechanism to establish a prediction model.

3.1. Prediction of Fashion Element Trend Based on Coexistence Relationship. The method of automatically extracting unified popular element labels from image data is crucial for the accuracy and efficiency of trend prediction. At the same time, the trend changes of one party in the coexistence relationship will affect the other party, so the study aims to strengthen the ability of trend prediction based on the coexistence relationship of clothing elements. The main issue that needs to be addressed in research is how to predict trends through visual images. The primary task for any given clothing photo is to identify the corresponding popular elements [17]. The method adopted by the research institute is to learn a predictor based on the EfficientNet-B7 model, which can accurately extract clothing fashion element attributes in the target image. EfficientNet is a new type of neural network model that is obtained through reinforcement learning of the MnasNet model and the use of composite scaling rules. It is suitable for performing multi label classification tasks.

In the multi-label classification problem for identifying clothing popular element attributes, the neural network training process uses a binary cross entropy loss function, as shown in formula (3.1).

$$\begin{cases} Loss_{BCE} = \{l_{1,c}, l_{2,c}, \cdots, l_{N,c}\}^T \\ l_{n,c} = -w_{n,c}\left[p_c y_{n,c} \bullet \log(x_{n,c}) + (1 - y_{n,c}) \bullet \log(1 - \sigma(x_{n,c}))\right], n = 1, 2, \cdots, N \end{cases} \tag{3.1}$$

In order to accelerate the update speed of model parameters, it is necessary to adjust the learning rate of the model reasonably. Here, we use the Adaptive Moment Estimation (Adam) algorithm for dynamic adjustment, which ensures that the model quickly approaches the optimal results in early training and steadily reaches the optimal state in later stages. By predicting the attributes of clothing popular elements, rich element attribute information can be obtained, which provides a good foundation for predicting the trend of clothing popular elements. The study constructs a model to predict elements trend with BiLSTM by using predicted clothing fashion elements from visual images as the data source for trend prediction. Figure 3.2 shows model's architecture.

At any specific point in time, the input information of the model includes many factors such as user characteristics g, clothing fashion element characteristics o, time characteristics m_t, and popularity y_t. These features are integrated into a feature embedding as v_t^e, as shown in formula (3.2).

$$v_t^e = [g, o, m_t, y_t] \tag{3.2}$$

In formula (3.2), the input sequence $v_t^e \in R^{5D+1}$of time$t$. The hidden representation of the input sequence

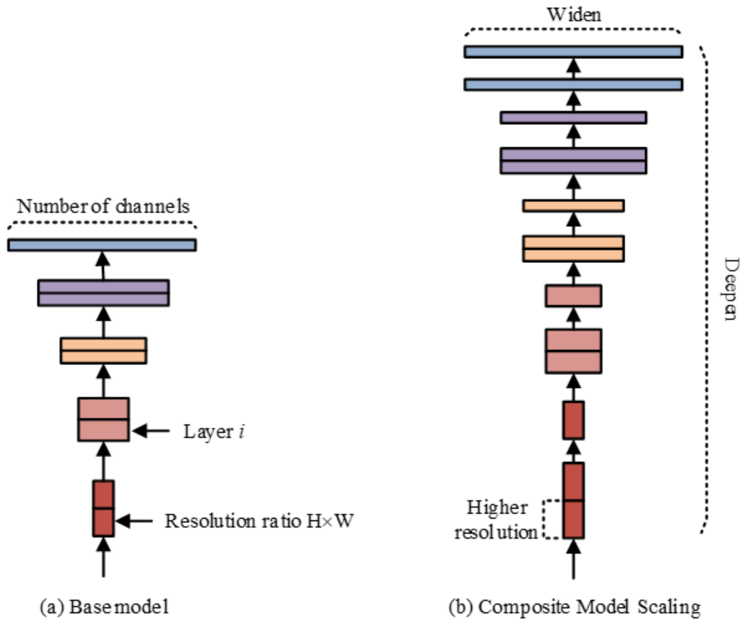


Fig. 3.1: Schematic Diagram of Composite Scaling Rulesn

at time t is the output data of the encoder LSTM, as shown in formula (3.3).

$$h_t^e = LSTM^e\left(v_t^e; h_{t-1}^e\right) \tag{3.3}$$

In formula (3.3), $h_t^e, h_{t-1}^e \in R^H$.

The decoder is mainly based on BiLSTM, and its initial hidden state is derived from the encoder's final output hidden state h_T^e. The mission of the decoder is to decode the input features made by the encoder and then output predicted trends of popular elements in the future $t \in [T, T']$. The input of the decoder includes the predicted user population, popular element features, and the connection characteristics of the time feature sequence, as shown in formula (3.4).

$$v_t^d = [g, o, m_t] \tag{3.4}$$

In formula (3.4), the characteristic at this time$v_t^d \in R^{3D+1}$. The evolution of BiLSTM on traditional LSTM lies in its ability to integrate past and future information through bidirectional learning, thereby better grasping the contextual information of trend sequences. The forward information transmission representation is shown in formula (3.5).

$$\begin{cases} \vec{h}_t^d = LSTM\left(v_t^d; \vec{h}_{t-1}^d\right) \\ \overleftarrow{h}_t^d = LSTM\left(v_t^d; \overleftarrow{h}_{t+1}^d\right) \\ h_t^d = LSTM\left(\vec{h}_t^d; \overleftarrow{h}_t^d\right) \end{cases} \tag{3.5}$$

In formula (3.5), $\vec{h}_t^d, \vec{h}_{t-1}^d, \overleftarrow{h}_t^d, \overleftarrow{h}_{t+1}^d \in R^H, h_t^d \in R^{2H}$. The final prediction result is based on the final hidden state of each step in the encoding and decoding stage during the training process. During model testing,

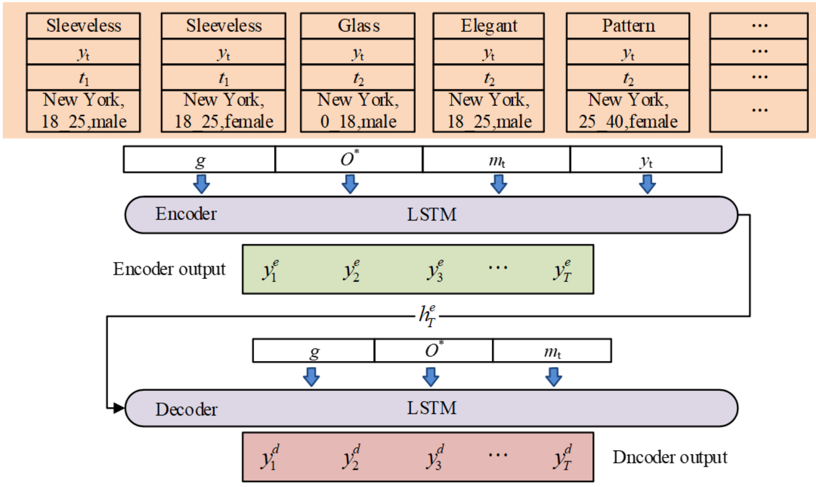


Fig. 3.2: Schematic Diagram of the Architecture of a Fashion Element Trend Prediction Model

predictions are only made during the decoding phase. The predicted results are characterized by using a linear layer for output during the encoding and decoding stage, as shown in formula (3.6).

$$\begin{cases} y_t^e = W_e h_t^e + b_e \\ y_t^d = W_d h_t^d + b_d \end{cases} \tag{3.6}$$

In formula (3.6), $W_e \in R^H$, $W_d \in R^{2H}$ is the weight represented linearly. b_e and b_d are biases represented linearly. During the entire model training process, we used L1 loss to optimize the model, and the total loss $Loss^*$ of the model includes the loss $Loss_{enco}$ of the encoder and the loss $Loss_{deco}$ of the decoder, as shown in formula (3.7).

$$Loss^* = Loss_{enco}\left(y_e, y_e^*, \theta_e\right) + Loss_{deco}\left(y_d, y_d^*, \theta_d\right) \tag{3.7}$$

In formula (3.7), θ_e and θ_d are the parameters of the encoder and decoder models, respectively. y_e and y_d are the true values of popularity in decoders and decoders. Predicted values for popularity in encoders and decoders. In fact, not all clothing elements are independent attributes. The study constructs a probability matrix by calculating the coexistence relationship between clothing attributes, in order to introduce the co-existence relationship into the prediction model. The number of simultaneous occurrences of two elements in one year's historical data is $N_{a,b}$. The number of occurrences of elements a is N_a, and the number of occurrences of elements b is N_b. The influence of elements b on elements a is expressed as $P_{a,b} = N_{a,b}/N_a$. The probability of the influence of an element a on the element b is expressed as $P_{b,a} = N_{a,b}/N_b$. The previously constructed elements are represented by vectors α, and the relationships between elements are transferred in the embedded representation. The original information and propagation information are represented by linear layer aggregation α^*, as shown in formula (3.8).

$$\alpha^* = W_e\left[\alpha, \alpha W_{ele}\right] + b_e \tag{3.8}$$

In formula (3.8), W_e and b_e are the weight matrices and biases of the linear representation layer. Therefore, the final representation of the encoder's input is shown in formula (3.9).

$$v_t^e = [g, \alpha*, m_t, y_t] \tag{3.9}$$

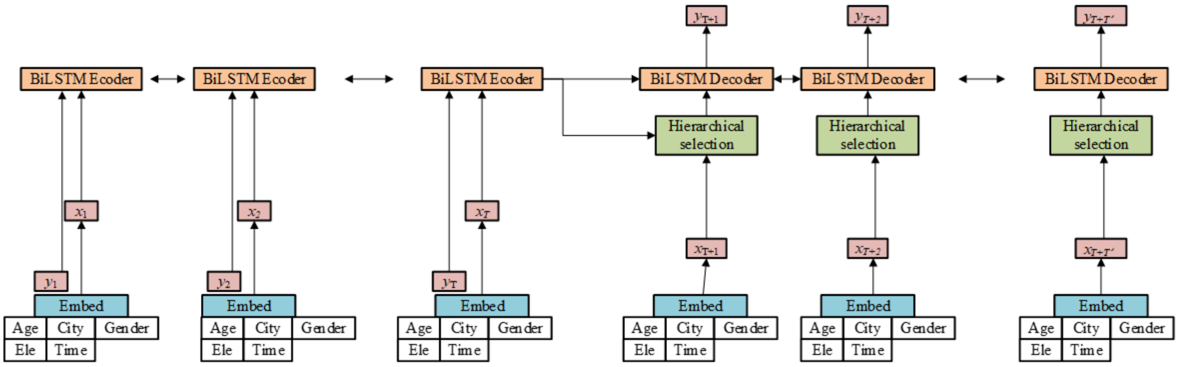


Fig. 3.3: Schematic Diagram of the Architecture of Similarity-Based Model

3.2. Fashion Element Trend Prediction Model Introducing AM. Elements trend prediction mostly relies on analyzing and learning past data, and then predicting future trends based on these patterns. However, if too much historical information is accumulated, the ability to capture the main information may be lost, leading to unsatisfactory prediction results [18]. The introduction of attention mechanism, just like the human way of attention, mainly focuses on some important information, which improves the predictive ability of the model. One of the characteristics of clothing fashion element data is xt=[a, c, s, o, 4], and it can be seen that the only part that changes is time. If time is only the main focus, other trends in periodic changes will be ignored. Therefore, the method adopted in the study is to find the historical information closest to the predicted trend based on the periodic changes in fashion trend elements and similar life cycle characteristics, and pay special attention to the trend changes during this period in the prediction. The main goal of the study is to find hidden patterns and interaction patterns among various elements in historical fashion trend information, in order to predict future trend information. In practical applications, the research adopts a structure to learn historical information, and the model architecture is shown in Figure 3.3.

In conjunction with the analysis in Figure 3.3, it can be seen that in carrying out the design process of the decoder, the study incorporated a channel that incorporates both attentional and temporal hierarchies. Utilizing this channel enables trend comparisons to be made, thus effectively assessing the importance of historical trend information to the current forecast information.

By characterizing the features in the historical information, it is possible to make better predictions about the changing trends. Also in problem processing, given historical data, users are grouped by age, city, and gender, with each group containing multiple clothing elements. In terms of problem handling, users are grouped after the given historical data, with each group containing different elements.

The popularity of an element in one of the groups at the current time point t is defined as $y_t = N_t^{g,o}/N_t^g$. Among them, $N_t^{g,e}$ count elements o in the user group g at the time t, and N_t^g counts all o owned by g at t. Therefore, the problem studied becomes a model $f(\bullet)$ learning for popularity prediction within a given time series $[T+1, T+T']$ over a time range $[1, T]$, $T' > 1$ is the predicted time range.

Embedding methods are used to convert limited grouping information into different digital vectors. Encode classification features using one hot encoding method. The three attributes contained in each user group are converted into feature embeddings a, c, s. Among them, a, c, and s respectively represent age, city, and sex. At the same time, fashion popular elements are also transformed into o. In this way, encoder's input is a combination of a, c, s, o, and time features l_t at each time $t \in [T_1, T_t]$ with historical trend values y_t. The encoded input is passed through BiLSTM, where the hidden layer of the forward LSTM at time t is denoted as, and that of the backward LSTM as. Hidden layer state update representation can be observed in formula

(3.10).

$$\left\{\begin{array}{l}\vec{h}_t = LSTM\left(\hat{x}_t; \vec{h}_{t-1}\right) \\ \overleftarrow{h}_t = LSTM\left(\hat{x}_t; \overleftarrow{h}_{t+1}\right) \\ h_t = LSTM\left(\vec{h}_t; \overleftarrow{h}_t\right)\end{array}\right. \tag{3.10}$$

The prediction model proposed in the study adopts a novel hierarchical temporal attention mechanism. This mechanism improves the accuracy of prediction by trend similarity comparison between the recent time period T_l and historical information T_h, and selecting subsequent information $T_h + T^*$ of the T_h historical information that is closest to the T_l time period as the key factor affecting future trends. Based on the historical information of the past N years, the fashion trend for the following year is predicted, and the annual historical data includes $M = 24$ time nodes. Y_i is used to represent the trend data of the i-th year, Y_l to represent those of the most recent year, and $\bar{Y}$ to represent the average of annual trend information. So, the trend similarity $D\left(Y_i, Y\right)$ for year i is shown in formula (3.11).

$$D\left(Y_i, Y\right) = \sum_{j=1}^{M} \left\|y_{i,j} - y_j\right\|_2, i = 1, 2, \cdots, N \tag{3.11}$$

In formula (3.11), when $i < N$, $Y = Y_l$ and $y = y_l$. Then, the weight of historical information for different years is represented by the reciprocal method, as shown in formula (3.12).

$$\left\{\begin{array}{l}\eta_i = \frac{\exp(D(Y_N,Y))}{\sum_{i=1}^{N}\exp(D(Y_i,Y))}, i = 1 \\ \eta_i = \frac{\exp(D(Y_{i-1},Y))}{\sum_{i=1}^{N}\exp(D(Y_i,Y))}, i = 2, \cdots, N\end{array}\right. \tag{3.12}$$

By using attention mechanisms, it is possible to extract more useful historical information for predicting current trends. For the data j in year i, the calculation of attention weight $\rho_{i,j,t}$ is shown in formula (3.13).

$$\rho_{i,j,t} = \frac{\exp\left(d_{i,j,t}\right)}{\sum_{i=1}^{N}\sum_{j=1}^{M}\exp\left(d_{i,j,t}\right)} \tag{3.13}$$

In formula (3.13), $\rho_{i,j,t}$ is the $(i \times M + j)$-th element of vector $d_t = \left(d_t^1, d_t^2, , d_t^M\right)$. The vector d_t is shown in formula (3.14).

$$d_t = V_d \tanh\left(W_d\left[h_{t-1}^d; x_t\right]\right) \tag{3.14}$$

In formula (3.14), the weight matrices V_d and W_d are obtained through model joint training. h_{t-1}^d is the decoder hidden vector at $t-1$. To convert hidden information into predicted outputy^*, a fully connected layer is utilized, which incorporates a calibrated linear unit with ReLU activation function, as shown in formula (3.15).

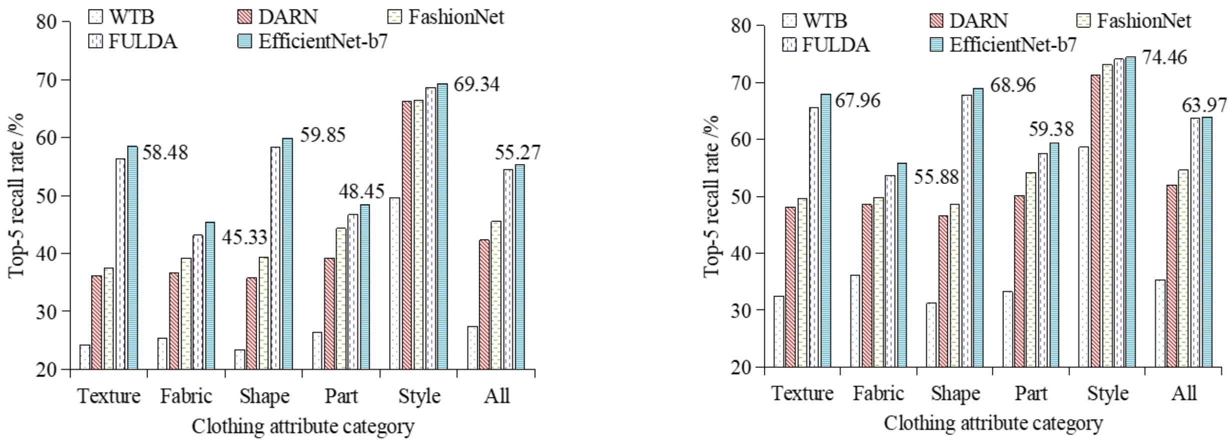
$$y^* = V_y \mathrm{ReLU}\left(W_y h_{T+1,T+T'}^d\right) \tag{3.15}$$

In formula (3.15), $h_{T+1,T+T'}^d$ denotes hidden state. The study uses L1 paradigm to train the entire model, including encoder loss and decoder loss.

4. Validation of the Fashion Element Trend Prediction Model Based on AM Fusion EfficientNet-b7. The study validated the effectiveness of the fashion element trend prediction model based on AM fusion EfficientNet-b7. The experiment includes two parts: analysis of clothing element attribute popularity prediction model based on coexistence relationship and analysis of clothing element popularity trend prediction model. For experimental verification, the DeepFashion dataset was first used for model training, and algorithms such as Mean, Last, Autocompression (AR), Vector Autocompression (VAR), Exponential Smoothing (ES), Linear, and GeoStyle were selected as comparison methods. The performance evaluation indicators of the model are Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

Table 4.1: Parameter Settings for the Experiment

Number	Parameter	Element Attribute Prediction	Trend prediction	Trend prediction (improved)
1	Embedding size of features	/	128	10
2	Optimizer	Adam	Adam	Adam
3	Initial Learning rate	0.001	0.001	0.001
4	Weight Decay	5e-4	5e-4	5e-4
5	Size of hidden layers	/	50	120
6	Epoch	1000	100	100



(a) Top-3 recall rate for fashion element attribute popularity prediction

(b) Top-5 recall rate for fashion element attribute popularity prediction

Fig. 4.1: Top-k Recall Rate for Fashion Element Attribute Popularity Prediction

4.1. Validity Testing of a Fashion Element Trend Prediction Model Using Coexistence Relationship. The effectiveness validation experiment of the fashion element trend prediction model based on coexistence relationship was divided into fashion element attribute trend prediction and fashion element trend prediction. The study is based on clothing elements in a coastal city in China, while model training is performed using the DeepFashion dataset, and trend prediction is performed using clothing images of 2,500 users collected from social networking sites. There were a total of 800000 images and 1000 clothing attributes in the DeepFashion dataset, with 6:1 images in the training and validation sets. The collected clothing images were divided, with 16 cities and 4 groups based on ages of 18, 25, and 40. The statistical frequency of popularity was 15 days per occurrence, and a total of 264 time nodes were obtained from the eleven year data. The Top-k recall rate was the top-k attribute obtained by sorting the classification results obtained after 1000 classifications from a minimum to a minimum. The parameter settings for the experiment are shown in Table 4.1.

The recall rate obtained from the popular prediction of clothing element attributes is shown in Figure 4.1. From Figure 4.1, it can be observed that the model proposed based on EfficientNet-b7 had high predictive accuracy in all fashion element attributes. Its top-3 recall rate was 69.34%, higher than other models. The top-5 recall rate was 63.97%, which was also at a relatively high level. This indicates that the prediction model performed better in predicting the popularity of clothing element attributes as a whole.

The study selected algorithms such as Mean, Last, Autocompression (AR), Vector Autocompression (VAR), Exponential Smoothing (ES), Linear, and GeoStyle for comparative experiments on element trend prediction. The Mean and Last algorithms took the average and last numerical values of the test data as the predicted

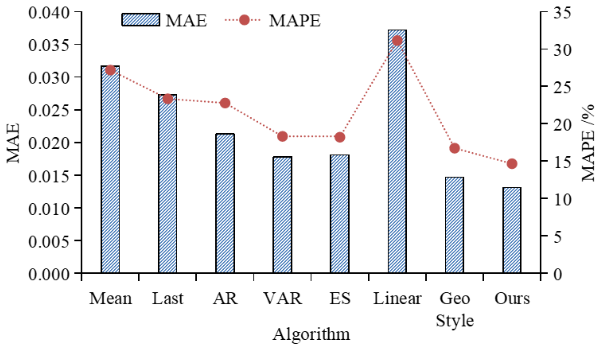


Fig. 4.2: Results of Comparative Experiments on Fashion Element Trend Prediction

Table 4.2: The Results of the Ablation Experiment

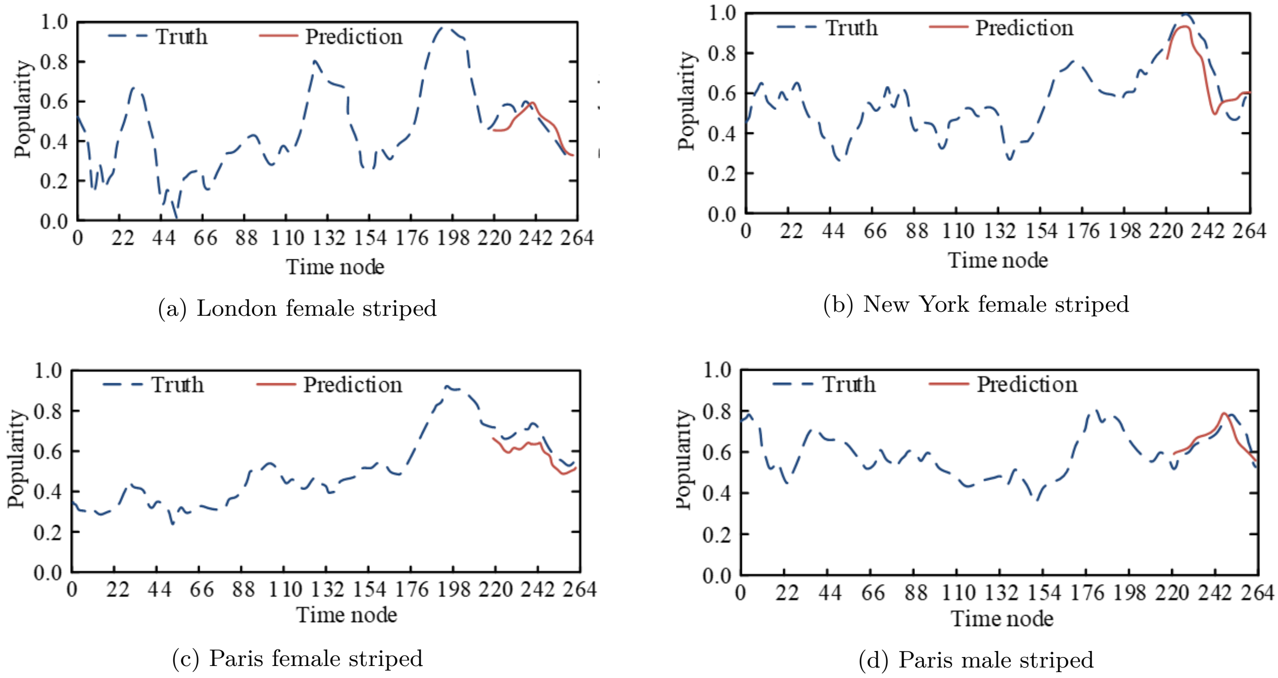
Number	Group	MAE	MAPE
1	User	0.0145	15.91
2	Relation	0.0136	15.03
3	Ours	0.0132	14.68

values, respectively. The results of the comparative experiment are shown in Figure 5. From Figure 4.2, it can be seen that the GeoStyle method had the best MAE performance at 0.0147, while the proposed method had the best performance on MAPE at 14.67%. Overall, the method proposed in the study performed significantly better on two indicators than other methods. This indicates that compared to other methods, this method had a more accurate and reliable predictive ability for fashion element trends.

The results obtained by removing the predictive power of some design models from the unified dataset are shown in Table 2. Among them, User represents the removal of user grouping processing, and Relation represents the removal of coexistence relationships between fashion elements. From Table 4.2, it can be seen that the model considering coexistence relationship performed best in both MAE and MAPE, with values of 0.0132 and 14.68%, respectively. This indicates that the coexistence relationship of elements can help improve the performance of prediction models.

Specifically, the trend of contrasting stripe attributes is shown in Figure 6. From Figure 6, it can be seen that there were differences in the historical trends of different elements after grouping users, reflecting trend prediction necessity for user grouping. Observing the results of trend prediction, the trend changes predicted by the research institute for six months were basically consistent with the actual trend.

4.2. Performance Test of Fashion Element Trend Prediction Model Introducing Trend Similarity AM. The effectiveness validation experiment of the fashion element trend prediction model using trend similarity AM was conducted using the FIT dataset. This dataset included 680000 clothing images collected from social media platforms, as well as information on users' gender, age, and city. The frequency of prevalence statistics was still 15 days per occurrence, and the dataset covered a period of 5 years. The comparative algorithms selected for the study include Mean, Last, AR, VAR, ES, Linear, and the Combination of Internal and External Knowledge (CIEK) model. The results of the comparative experiment are shown in Figure 4.4. From Figure, it can be seen that the Ours model was the best performing model in predicting the trend of six months, with lower MAE and MAPE values compared to other models. In the one-year trend prediction, the Ours model also outperformed other models in MAE and MAPE, with high prediction accuracy and reliability. The improvement in short-term trend prediction ability of the model was greater, due to the small amount of prediction data generated by short-term trend prediction and the small error it brought.



(a) London female striped

(b) New York female striped

(c) Paris female striped

(d) Paris male striped

Fig. 4.3: Trend and Prediction Results of Stripe Attributes in Different Cities

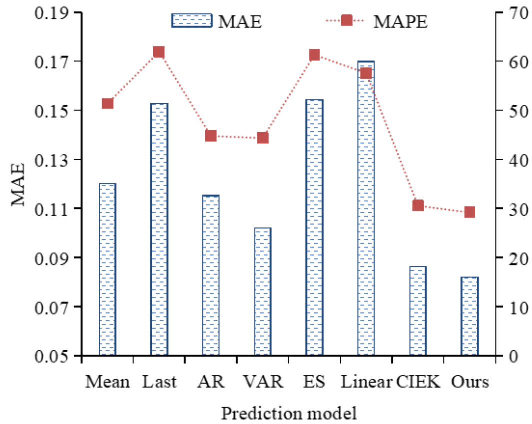
Figure 4.5 shows the model predicted results, with the first three subgraphs showing the predicted trends of different elements in same group. Figures 8 (c) and 8 (d) show the predicted trends of the same element in different user groups. From Figure 4.5, it can be seen that the clothing trend prediction model based on trend similarity proposed in this chapter can fit future trend changes. At the same time, it can be clearly seen that short-term forecasting has better results.

Clothing fashion elements trend among different user groups is shown in Figure 4.6. From Figures 4.6 (a), (b), and (c), it can be seen that the trend changes corresponded to different ages, cities, and genders, with some time periods showing opposite trends, indicating the necessity of grouping users into predictions.

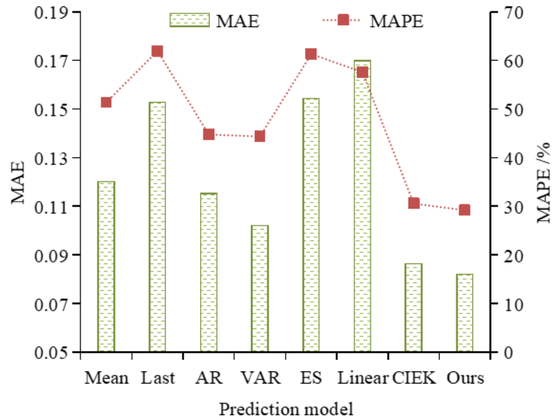
The prediction model based on trend similarity attention mechanism proposed in the study showed good predictive ability, especially for clothing elements with obvious periodicity. Figure 4.7 illustrates the forecast of purple clothing components among women aged 18 to 25 in Shanghai. It can be seen that elements prediction with less periodicity still needed improvement, and a significant downward trend cannot be predicted at the beginning. The reason for the existence of this situation was based on the attention mechanism of trend similarity, which focused on the obvious periodicity of most clothing fashion elements. For clothing fashion elements with less periodicity and long-term trend prediction, the improvement of prediction accuracy was not high.

As shown in Table 4.3 are the validation indicators used in the study, and the values of the relevant indicators.

5. Discussion. The study utilizes the attribute predictor constructed by the EfficientNet-b7 model to quickly and accurately extract the attributes of elements on clothing images, and constructs the prediction model through the encoder-decoder framework of BiLSTM to achieve effective prediction of clothing fashion element trends. Meanwhile, the study further improves the performance of the prediction model by introducing the trend similarity attention mechanism. This indicates that this suggests a broad application of deep learning technology in apparel fashion element trend prediction. The variables also produced positive changes, and

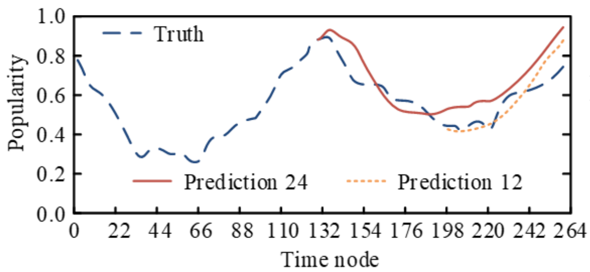


(a) Half Year Epidemic Trend Prediction Results

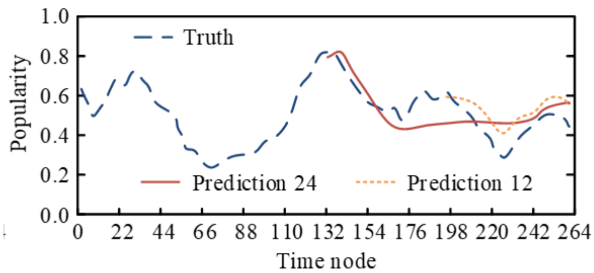


(b) One Year Epidemic Trend Prediction Results

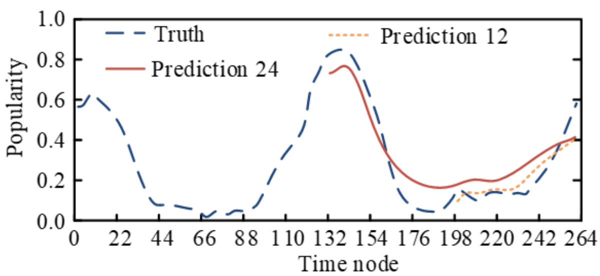
Fig. 4.4: Prediction Results of Fashion Element Trends by Different Models



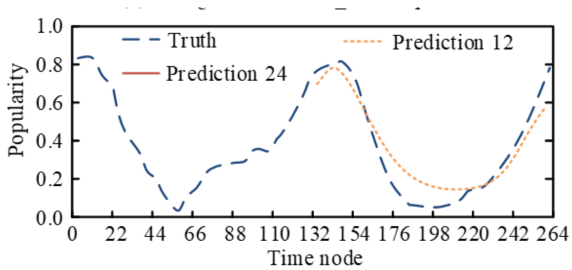
(a) Shanghai female 18_25 Sexy



(b) Shanghai female 18_25 Shape: Pencil



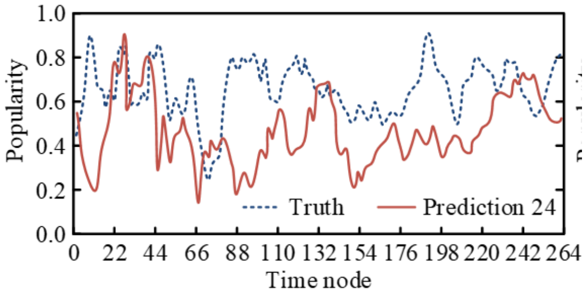
(c) Shanghai female 18_25 Sleeve_length: short



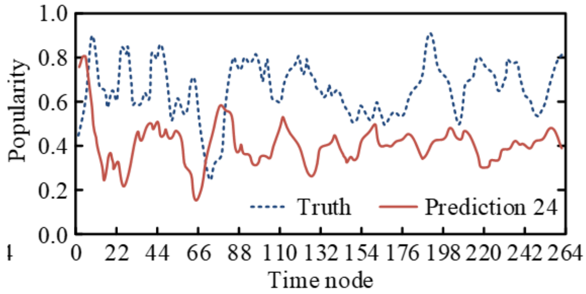
(d) New York female 25_40 Sleeve_length: short

Fig. 4.5: Prediction Results of Similarity-based Fashion Trend Prediction Model

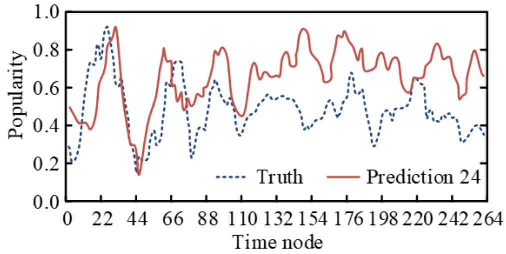
the study found that the model considering coexistence relationships performed best in terms of MAE and MAPE by comparing the prediction results of different models, which were 0.0132 and 14.68%, respectively. In the study of accuracy, the model with the introduction of the trend similarity attention mechanism showed a significant improvement in accuracy by 5.09% and 4.54%. This shows that these theories and changes provide new ideas and methods for the field of clothing design and art design. Through the study, it was found that



(a) Trends in streetstyle elements among Shanghai women of different ages



(b) Trends in streetstyle elements among women aged 18 to 25 in different cities



(c) Trend in gray elements in Shanghai between different genders of 25 to 40

Fig. 4.6: Trends in Fashion Trends among Different User Groups

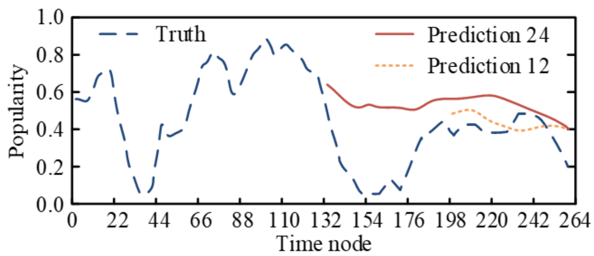


Fig. 4.7: Prediction Results of Purple Clothing Elements among Shanghai Women Aged 18 to 25

the limitations of the application of the fashion trend prediction model for clothing elements, which integrates AM and EfficientNet-b7 models, in fine art design are mainly data collection and labeling, model complexity, and real-time response. The model can be applied in the fields of fashion design, apparel design, and apparel matching to help designers predict future apparel trends and enhance the market competitiveness of their design works.

6. Conclusion. With the continuous development of computer technology and the arrival of the big data era, trend prediction through data-driven methods has gradually shown advantages. The research aims to use deep learning technology to predict fashion elements trend. Therefore, this study first constructs an attribute predictor based on the EfficientNet-b7 model, which is used to quickly and accurately extract element attributes from clothing images, and to use the coexistence relationship between clothing popular elements

Table 4.3: Results of relevant validation indicators

Sports event	Optimum value	Minimum value
Recall rate	69.34%	63.97%
MAE value	0.0147	0.0132
MAPE value	14.68%	14.67%
Popularity expectations	1.0	0.79

to assist in prediction. Then, based on user information, clothing fashion elements are grouped and counted to construct a prediction model based on the BiLSTM encoder decoder framework to train trend information as a whole. Results showed that the model considering coexistence relationship performed best in MAE and MAPE, with values of 0.0132 and 14.68%, respectively. In addition, the attention mechanism based on trend similarity also had certain effects in improving model performance, with an accuracy improvement of 5.09% and 4.54% compared to the latest KERN model. By combining attribute predictors, user information, coexistence relationships, and trend similarity, clothing trends can be accurately predicted. Designers can quickly select the most suitable materials and improve design efficiency by predicting fashion fashion trends during art design. However, the coexistence relationship between clothing fashion elements proposed in the study is only a simple relationship, which can be further explored in subsequent work and applied in trend prediction models.

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REFERENCES

[1] Tuite, R. The Hidden History of American Fashion: Rediscovering 20th-Century Women DesignersThe Fashion Forecasters: A Hidden History of Color and Trend Prediction. *Ournal Of Design History.* **32**, 316-319 (2019)

[2] Leket, C. The Fashion Forecasters: A Hidden History of Color and Trend Prediction, edited by Regina Lee Blaszczyk and Ben Wubs. *The Design Journal.* **22**, 2019 (0)

[3] Cheng, W., Song, S., Chen, C., Hidayati, S. & Liu, J. Fashion meets computer vision: A survey. *ACM Computing Surveys (CSUR).* **54**, 1-41 (2021)

[4] Kaur, P., Harnal, S. & Tiwari, R. Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction. *Sensors.* **22**, 575-589 (2022)

[5] Mahaveerakannan, R., Anitha, C. & Thomas, A. An IoT based forest fire detection system using integration of cat swarm with LSTM model. *Computer Communications.* **211**, 37-45 (2023)

[6] Dongnan, Z., Di, Z., Nana, L. & Bing, H. Exploration of Three Incidence Trend Prediction Models Based on the Number of Diagnosed Pneumoconiosis Cases in China From 2000 to 2019. *Journal Of Occupational & Environmental Medicine.* **63** pp. 7 (2021)

[7] Guo, Y., Mustafaoglu, Z. & Koundal, D. Spam Detection Using Bidirectional Transformers and Machine Learning Classifier Algorithms. *Journal Of Computational And Cognitive Engineering.* **2**, 5-9 (2022)

[8] Shen, J. & Shafiq, M. Short-term stock market price trend prediction using a comprehensive deep learning system. *Journal Of Big Data.* **7**, 1-33 (2020)

[9] Xu, M., Du, J., Xue, Z., Guan, Z., Kou, F. & Shi, L. scientific research topic trend prediction model based on multi-LSTM and graph convolutional network. *International Journal Of Intelligent Systems.* **37**, 2022 (0)

[10] Picasso, A., Merello, S., Ma, Y., Oneto, L. & And, C. and sentiment embeddings for market trend prediction. *Expert Systems With Applications.* **135** pp. 60-70 (2019)

[11] Hu, Y., Sun, X., Nie, X., Li, Y. & Liu, L. An enhanced LSTM for trend following of time series. *IEEE Access.* **7** pp. 34020-34030 (2019)

[12] Dong, M., Zeng, X., Koehl, L. & Zhang, J. An interactive knowledge-based recommender system for fashion product design in the big data environment. *Information Sciences.* **540** pp. 469-488 (2020)

[13] Wu, D., Li, Z., Zhou, J., Gan, J., Gao, W. & Li, H. Clothing attribute recognition via a holistic relation network. *International Journal Of Intelligent Systems.* **37**, 6201-6220 (2022)

[14] Lu, S., Zhu, X., Wu, Y., Wan, X. & Gao, F. Outfit compatibility prediction with multi-layered feature fusion network. *Attern Recognition Letters.* **147** pp. 150-156 (2021)

[15] Yang, S. & Jang, S. Fashion trend forecasting using ARIMA and RNN: application of tensorflow to retailers' websites. *Asia Life Sci.* **18** pp. 407-418 (2019)

[16] Hanif, R., Mustafa, S., Iqbal, S. & Piracha, S. study of time series forecasting enrollments using fuzzy interval partitioning method. *Journal Of Computational And Cognitive Engineering.* **2**, 143-149 (2023)

[17] Fang, Y., Luo, B., Zhao, T., He, D., Jiang, B. & St-and, L. and interaction graph aggregation for multi-agent perception and trajectory forecasting. *CAAI Transactions On Intelligence Technology.* **7**, 744-757 (2022)

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