Research on fabric classification based on graph neural network

DOI: 10.35530/IT.074.01.202224

PENG TAO
CAO WENLI
CHEN JIA
LV XINGHANG
ZHANG ZILI
LIU JUNPING
HU XINRONG

ABSTRACT – REZUMAT

Research on fabric classification based on graph neural network

Fabric classification plays a crucial role in the modern textile industry and fashion market. In the early stage, traditional neural network methods were adopted to identify fabrics with the drawback of restricted fabric type and poor accuracy. Combining multi-frame temporality and analysing fabric graph data made from fabric motion features, this paper proposes a novel hybrid model that introduces the concept of graph networks to classify 30 textile materials in a public database. We utilize the graph inductive representation learning method (GraphSAGE, Graph Sample and Aggregate) to extract node embedding features of the fabric. Moreover, bidirectional gated recurrent unit and layer attention mechanism (BiGRU-attention) are employed in the last layer of aggregation to calculate the score of previous cells. Intending to further enhance performance, we link the jump connection with adaptive selection aggregation frameworks to determine the influential region of each node. Our method breaks through the limitation that the original methods can only classify a few fabrics with great classification results.

Keywords: *fabric classification, multi-frame temporality, fabric graph data, GraphSAGE, BiGRU-attention*

Cercetări privind clasificarea materialelor textile pe baza rețelei neuronale grafice

Clasificarea materialelor textile joacă un rol crucial în industria textilă modernă și pe piața modei. În faza incipientă, metodele tradiționale ale rețelelor neuronale au fost adoptate pentru a identifica materialele textile cu dezavantajul tipurilor limitate de material textil și al preciziei scăzute. Combinând temporalitatea cu cadre multiple și analizând datele grafice ale materialului textil realizate din caracteristicile de mișcare ale acestuia, această lucrare propune un model hibrid nou care introduce conceptul de rețele grafice pentru a clasifica 30 de materiale textile într-o bază de date publică. Am utilizat metoda de învățare a reprezentării prin inducție grafică (GraphSAGE, Graph Sample și Aggregate), pentru a extrage caracteristicile nodurilor materialului textil. În plus, unitatea recurentă bidirecțională și mecanismul de atenție a stratului (BiGRU-attention) au fost utilizate în ultimul strat de agregare pentru a calcula scorul celulelor anterioare. Obiectivul nostru a fost de a îmbunătăți și mai mult performanța, de a lega conexiunea de salt cu cadrele de agregare a selecției adaptive, pentru a determina regiunea influentă a fiecărui nod. Metoda noastră depășește limitarea conform căreia metodele originale pot clasifica doar câteva materiale textile cu rezultate excelente de clasificare.

Cuvinte-cheie*: clasificarea materialelor textile, temporalitate cu cadre multiple, date grafice ale materialelor textile, GraphSAGE, BiGRU-attention*

INTRODUCTION

Fabric classification takes a wide range of applications in textile manufacturing. In the early period, investigators classified textile materials by manual operations, such as sensory, combustion, etc. which involved certain subjectivity and irreversibility. With the enrichment of variety for textiles increasingly, the current research hotspot is turned to exploring an intelligent, efficient, and exact identification strategy for textile fibres.

The study of textile material recognition has aroused broad concern in recent years [1–3]. Generally speaking, the research can be divided into two categories: static fabric recognition and dynamic fabric recognition.

Fabric recognition based on static images

Han et al. [4] segmented the colour and spatial information of fabric images and then performed wavelet transform in line with the frequency components contained in the secondary and tertiary wavelet decomposition layers to distinguish rough fabrics. Jing et al. [5] proposed extracting fabric texture features through a moving grey-level co-occurrence matrix (GLCM) and Gabor wavelet, sorting the three basic fabrics with a probabilistic neural network (PNN). The above studies mainly considered the shape and texture characteristics of textiles, which were restricted to the recognition of several fabrics in specific scenes.

Fabric recognition based on dynamic videos

Bouman et al. [6] put forward a framework for estimating material properties with fabric videos, which withdrew surface information from inputs to train the model systematically. The key element overlooked in their work was multi-frame motion information. Yang et al. [7] classified fabrics by recording the change of external features as they swing, combining the feature extraction method of the image signal (i.e. CNN, Convolutional Neural Network) with the time series learning method (i.e. LSTM, Long Short-Term Memory). The existing issue was that the potential association of fabrics was not taken into account. Bi et al. [8] proved the significance of time sequence for material property evaluation by investigating the influence of the temporal and spatial features from multiple frames of motion on fabric bending and stiffness. However, the research focused on testing the relevance of the model to human perception rather than the classification of fabrics.

To solve the problems existing in previous approaches within the study of fabric classification, a method was first proposed by Tao et al. [9] that introduced the concept of the graph to describe the information of cloth motion characteristics. The graph is a ubiquitous structure that widely occurs in many fields including biology (protein-interaction networks) [10], chemistry (molecular graphs) [11], cognition intelligence (knowledge graphs) [12], social sciences (friendship networks) [13, 14] and other areas [15–17].

Compared to general classification algorithms such as CNN [18] and LSTM [19], the definition of graph neural network was originally proposed by Gori et al. [20] and Scarselli et al. [21] yet it had attracted much attention in recent years, breaking the limitation that the traditional network model can only handle Euclidean data, treating data with generalized topology structure on the contrary. It is worth mentioning that GCN_3 [9] took a heavy computation time to handle massive fabric structure data, the above work was still in the primary stage of textile material recognition study.

Inspired by these previous works and to address the shortcomings, we put forward a customized graph neural network model based on fabric graph data for the recognition and classification of textile material. The main contributions of our work are summarized as follows:

- For motion video-based fabric classification, we apply a fabric feature acquisition method that can be independent of fabric surface texture, structure, and colour factors, and convert Euclidean fabric video data into non-Euclidean fabric graph data by incorporating spatial feature information of fabric physical attributes while considering video temporality to achieve more efficient classification and recognition of fabrics with fewer memory resources.
- We are the first attempt to introduce the graph inductive representation learning method into fabric classification. At present, the general way of aggregation resulted in the fixed radius of influence cannot realize the optimal vector representation of each node and edge of the fabric graph. Hence, we combine the jump connection and adaptive aggregation mechanism so that nodes anywhere have the same chance to obtain rich information about neighbouring nodes.
- To further raise the robustness of the entire model, we introduce the bidirectional gated recurrent unit (BiGRU), optimize it with dropout for the avoidance of the vanishing gradient problem, and distinguish the significance of neighbour nodes in each layer via the merit of layer attention mechanism.
- In addition, we evaluate different performance metrics such as accuracy, precision, recall, F1-score and loss of the model with motion videos of 30 different fabrics as the experimental datasets. We further compare the proposed model with existing methods. The result demonstrates that our method realizes classification better as compared with other approaches.

The rest of this paper is organized as follows: in the second section, we describe the framework, dataset and data pre-processing details of our proposed model; in the third section, we introduce the setup and results of our experiments; in the fourth section, we present the discussion and comparison with other works; finally, the conclusion is drawn in the fifth section.

MATERIALS AND METHODS

Fabric force model

Most of the existing fabric recognition techniques rely on appearance characterization and multi-frame motion to determine the category, neglecting the role of its internal forces in estimating its properties. We thus perform force analysis for dynamic cloths to avoid the influence of external factors such as texture, colour, and light.

The fabric force model [9] is designed based on the framework of the social force model [22] for multi-particle self-driven systems. The model treats the fabric image as a composition of interrelated and uniformly distributed particles, and the fabric forms its motion trajectory as a result of the interaction forces of wind and tissue fibres, which leads to corresponding variations in the force flow of the particles, thereby obtaining fabric force flow information and classification in terms of motion characteristics. The model arranges the particle mesh on the fabric image, which is partially described in figure 1. Estimating the combined force of the moving particles with the fabric force model, the force analysis of particle *i* is shown in equation 1:

$$m_i \frac{dv}{dt} F_a = F_w + F_{int} \tag{1}$$

where F_a represents the actual force on the particle point, F_w stands for the wind force on the particle, and F_{int} denotes the interaction force on the particle

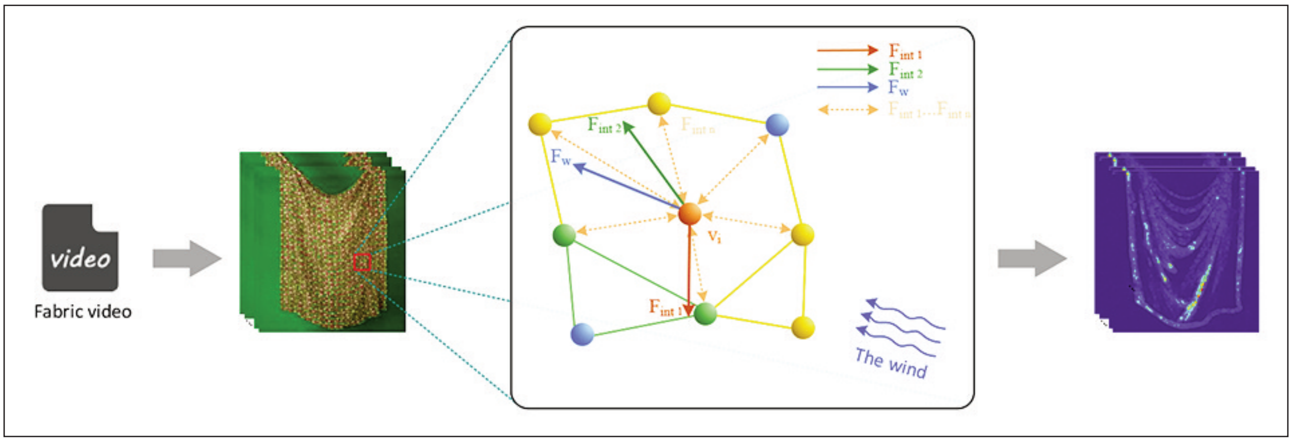

Fig. 1. Fabric stress analysis at time *t*

within the fabric, where F_{int} consists of the downward gravitational force on the particle point, the upward tensile force, the mutual repulsive force and tensile force between the particle points.

The actual speed of particle point *i* is related to the wind speed, but since *i* is also affected by internal tension, there is a difference between the actual speed v_i and the v_i^w generated under stable wind force, and the relaxation coefficient is defined to optimize the fabric wind force. The calculation formula of F_w is as follows:

$$F_w = \frac{1}{\tau}(v_i^w - v_i) \tag{2}$$

Each node *i* suffers from different wind forces, and w_i is introduced to represent the wind weight. When $w_i \rightarrow 0$, it means that the node is almost free from the wind, and $w_i \rightarrow 1$, it means that the wind force on the node is perpendicular to its gravity. Therefore, the velocity v_i^w produced under constant wind is replaced by v_i^m, and v_i^c stands for the average velocity of the adjacent nodes, which is shown in equation 3.

$$v_i^m = w_i v_i^m + (1 - w_i)(v_i^c) \tag{3}$$

In the fabric force model, the optical flow is taken to extract the interaction force F_{int} from the fabric video. The average optical flow length of each frame, O_{ave}, via the mean optical flow in a fixed space-time window and Gaussian weighted average in space. The actual speed v_i of particle *i* is the same as the size of the optical flow $O_{ave}(x_i, y_i)$ on the coordinate (x_i, y_i). By that, the motion speed of the particle *i* can be defined as equation 4.

$$v_i^m = w_i O_{ave}(x_i, y_i) + (1 - w_i) O_{ave}(x_i, y_i) \tag{4}$$

Corresponding coordinates (x_i, y_i) in the grid, where $O(x_i, y_i)$ denotes the valid temporal average of particle *i*, $O_{ave}(x_i, y_i)$ represents the single point optical flow value of particle *i*. The effective average flow field and effective optical flow between points are evaluated with the bilinear interpolation method. In the given fabric scene, the mass of particle *i* is set to $m_i = 1$. Thus, F_{int} is expressed as equation 5.

$$F_{int} = \frac{dv}{dt} - \frac{1}{\tau}(v_i^m - v_i) \tag{5}$$

Sample details

The dataset for the experiments is derived from the publicly available database of fabric videos with corresponding measured ground truth material properties [23, 24], which contains videos of 30 different textiles moving under three different winds. It is shown as the top two corners of the fabric fixed in the air and the same wind blowing in from the lower right position. Yet, the original fabric video as traditional Euclidean data cannot meet the requirements of the graph neural network model. We apply the fabric force model and visual word bag to convert it into non-Euclidean data, as shown in figure 2 or details.

Extract fabric movement characteristics

First, the continuous textile video was saved as a picture by frame with OpenCV, and then obtain the force flow diagram which combines the fabric force model. Next, cut the cropped image evenly into small $S \times S$ ($S \in \mathbb{R}^N$) image blocks with the slice tool, called it visual words. Last, calculate the RGB average value separately with each block as the unit in terms of the three primary colours.

Make the node feature list

Taking each frame as a graph node, filter and extract the visual words with representative fabric color features to generate a visual dictionary, which can be represented by $C = \{c_1, c_2, \dots, c_i, \dots, c_m\}$, where *C* stands for visual dictionary; C_i is the *i*-th visual word in the dictionary and a total number of visual words is *m*. Meanwhile, calculate and store the pixel values of RGB on each frame in force flow picture as visual words, $V = \{v_{1_1}, v_{1_2}, \dots, v_{1_T}, v_{2_t}, v_{2_{t+1}}, \dots, v_{c_1}, \dots, v_{c_T}\}$, where *i* is the video timing, *T* represents the total video duration, and *c* stands for the type of fabric number. According to the dictionary *C*, record 1 under the corresponding word c_i when it appears, and 0 otherwise. Thereby creating a node feature list by performing the above operations on all graph nodes.

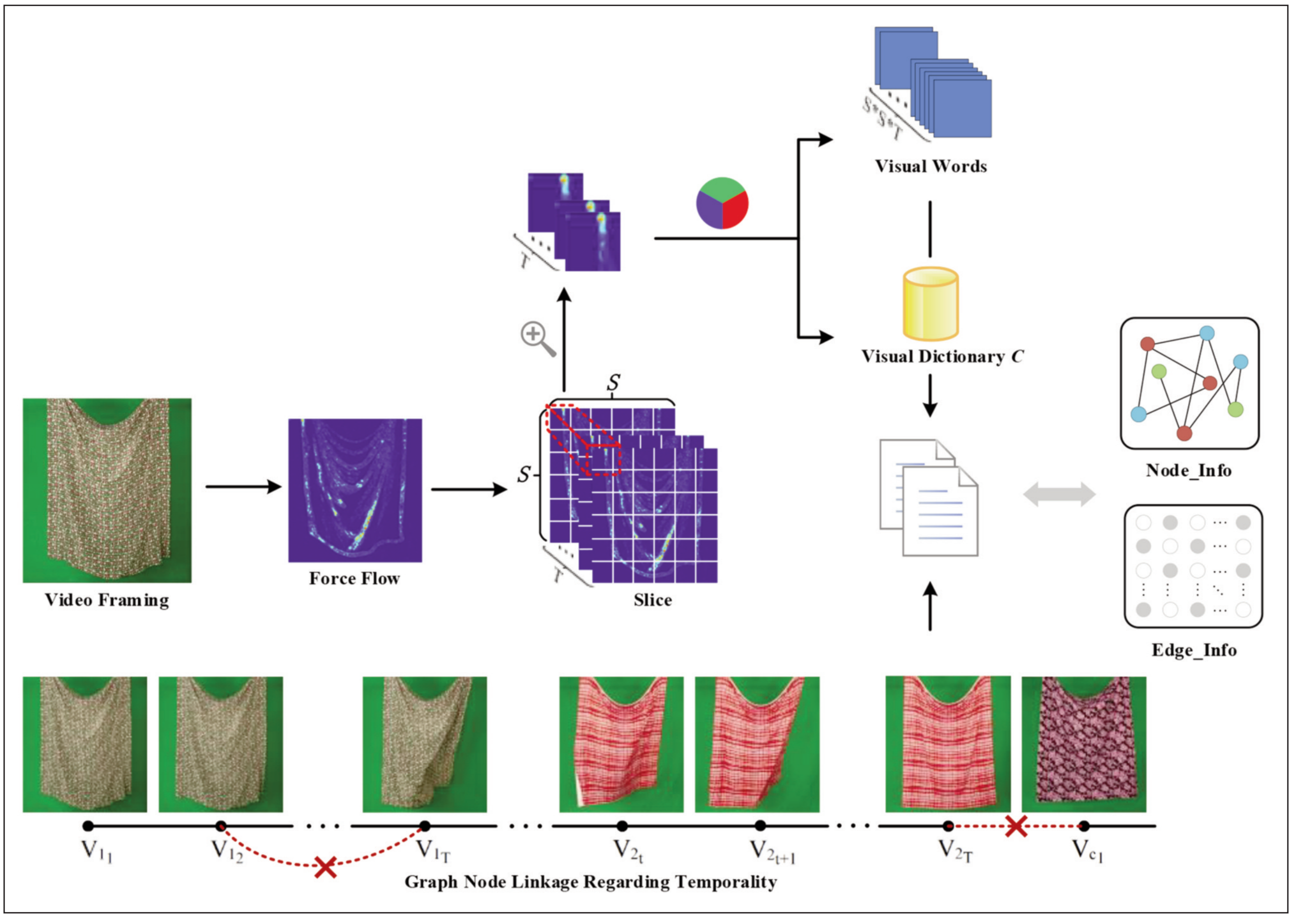

Fig. 2. Process of extracting fabric features from the video database

Construct fabric graph data

For various types of fabrics, rely on the visual word list to establish the connection between fabrics. If two nodes contain more than *Z* of the same visual word (*Z* is customized), there would be a certain similarity within them. For the same fabric judging by video temporality, like v_1 and v_2 are connected, as well as v_{2_t} and $v_{2_{t+1}}$ are connected, yet others are not connected such as v_{1_2} and v_{1_T} have no relation of time sequence.

With the above steps, each fabric video was processed into 2,700 images, and in total 81,000 fabric images are obtained. Considering each image as a graph node, when S = 6 and Z = 18, this database can generate 81,000 graph nodes and 2,916,000 visual words, and excluding duplicates, 2,230,516 words can be expanded the visual dictionary. As such, the object of our study is the fabric graph obtained from processing, i.e., node data containing force flow features and edge data representing association information. The nodes of the graph are randomly divided into a training set, a validation set and a test set in the ratio of 6:2:2, which are fed into a custom graph neural network.

Proposed model

Graph neural networks enjoy great popularity among scholars for their excellent performance in graphically structured data [25]. Graph convolutional network (GCN) [14, 26] retained the global structure of the graph as well as the attribute information of the node. Hamilton et al. [13] introduced GraphSAGE to concatenate features of the nodes and applied it to mean/max/LSTM operators for inductively learning node embeddings. Besides, Message Passing Neural Network (MPNN) by Gilmer et al. [27] further considered edge information when performing aggregation. Xu et al. [28] proposed a Jumping Knowledge Network (JK-Net) architecture in which the last layer of the model can selectively exploit information from neighbours at distinct locations, thus allowing a great capture of the node-level representation in a fixed number of graph convolution operations.

Furthermore, He et al. [29] introduced the Residual Network (ResNet) to skip layers for leveraging local information of different depths and hence can assist in model training, especially as the depth of the network increases. In summary, it can be seen that scholars have experimented with multiple parties on how to efficiently acquire graph node embedding features, which confirmed the credit of hierarchical level jump links in enhancing node learning ability.

The overall architecture of our model is shown in figure 3. We explore a hybrid architecture that efficiently generates unknown vertex embedding utilizing attribute information of vertices. Sample the neighbours of each vertex and aggregate the information contained therein to obtain the vector representation

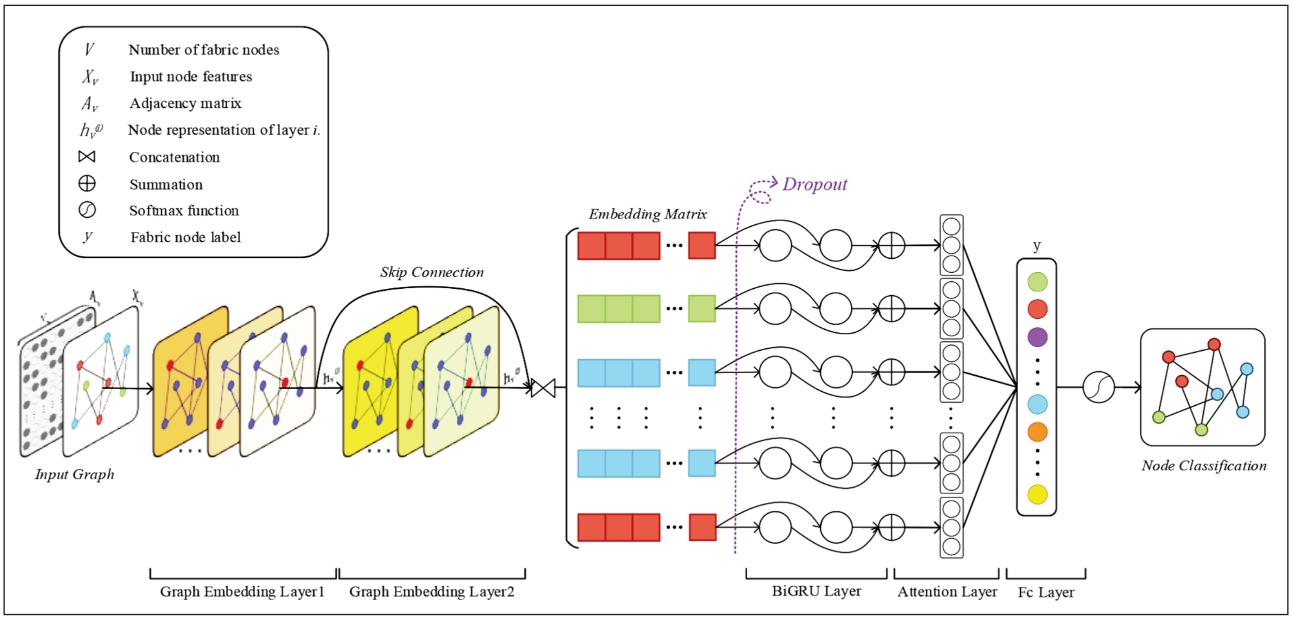

Fig. 3. The overall architecture of the proposed model

of each node in the graph. In the last layer of aggregation, each vertex filters some node feature information from embedded representations upstream and merges them selectively, i.e., the representations "jump" to the last layer. Each vertex independently performs this step to adjust its neighbourhood range, to obtain the adaptive capabilities that are required. We elaborate the details of our model by hierarchical order that illustrates the design of the bidirectional gated recurrent unit model with the attention mechanism. Applying a dropout layer after the embedding layer, the next layer is the BiGRU layer. Both GRU and LSTM are special variants of Recurrent Neural Networks (RNN) with logic gates. BiGRU-attention transmits the expression of each layer into the BiGRU so that each layer gets a forward representation and a backward representation, then sends them to the linear layer in series, and obtains the attention score of nodes in different neighbourhood ranges with softmax function, and finally receives the expression in weighting and summing.

EXPERIMENTS

Setup

The proposed model is trained and tested in NVIDIA Quadro M5000 with an 8 GB graphical processing unit (GPU), Intel(R) Xeon(R) CPU E5-2620 v3 @ 2.40 GHz, and 16 GB RAM. Our model is implemented by PyTorch and the details of the parameter required for the experiment are shown in table 1.

Results

To confirm the effectiveness of our customized method, we perform ablation comparisons in multiple experiments and choose five metrics generally applied for multi-classification tasks to measure the performance of the model including accuracy, precision, recall, F1-score, and loss (table 2).

Table 1

DETAILS OF THE EXPERIMENTAL PARAMETER

Parameter	Value	Description
Lr	0.005	Initial learning rate
Epoch	1000	Number of epochs
H_dim	64	Number of hidden units
Dropout	0.6	Dropout rate
Loss	NLLLOSS	Loss function
Optimizer	Adam	Adam Optimizer to train
Weight-decay	1e-7	L2 regulation weight

As it is known from [28] currently, the best performance of aggregation-based graph networks is two layers, and further layers would degrade the model performance. While GCN generates embedded features only for the current node during training, and cannot scale to unknown nodes, GraphSAGE provides an inductive framework by sampling and aggregating neighbouring vertices to generate embedding features for unknown nodes. According to the experimental data in table 2, regarding large-scale fabric graphs based on the same set of layer aggregation mechanisms, the accuracy, precision, and recall rate of two-layer GraphSAGE are slightly 0.5% higher than GCN, and the loss is slightly 2.4% lower. Besides, based on the same set of network embedding layers, we explore six mechanisms like concatenation, max-pooling, (Bi)LSTM-attention, and (Bi)GRU-attention. Concatenation is to connect the node representations of all layers in series and then perform a linear transformation. Yet, its transformation weights are equal for all nodes and cannot reach the adaptive effect. Max-pooling selects the most informative layer for each feature node, graph nodes

Table 2

COMPARISON OF ABLATION EXPERIMENT RESULTS						
Parameter		**Accuracy**	**Precision**	**Recall**	**F1-score**	**Loss**
Net.Layer	**Agg.Layer**					
GCN_2	Concat	0.939	0.943	0.918	0.930	0.384
	Max-pooling	0.943	0.947	0.924	0.935	0.257
	LSTM	0.951	0.952	0.933	0.942	0.220
	BiLSTM	0.953	0.958	0.941	0.949	0.208
	GRU	0.952	0.959	0.940	0.949	0.198
	BiGRU	0.957	0.961	0.933	0.947	0.193
$SAGE_2$	Concat	0.939	0.944	0.925	0.934	0.350
	Max-pooling	0.946	0.949	0.934	0.941	0.217
	LSTM	0.949	0.952	0.943	0.947	0.228
	BiLSTM	0.957	0.960	0.938	0.949	0.207
	GRU	0.955	0.958	0.935	0.946	0.191
Ours		**0.959**	**0.962**	**0.945**	**0.953**	**0.190**

that represent more local attributes can learn embedding information from the neighbourhood, while nodes representing global states prefer features from higher levels. From the perspective of the recurrent unit structure, GRU takes fewer connections and parameters throughout the network compared to LSTM, thus the model is more efficient with training and generalizing, and the BiGRU-attention is node-adaptive since each node has different attention scores. In short, BiGRU-attention is more suitable than the above five aggregation ways for large and complex fabric graphs.

From figure 4, we can notice more intuitively the comparison of classification accuracy and training loss in multiple ablation experiments. The experimental results show that our method has the best results in terms of precision, accuracy, recall, and F1 score, respectively, as well as the lowest loss of 19.8% for the whole group.

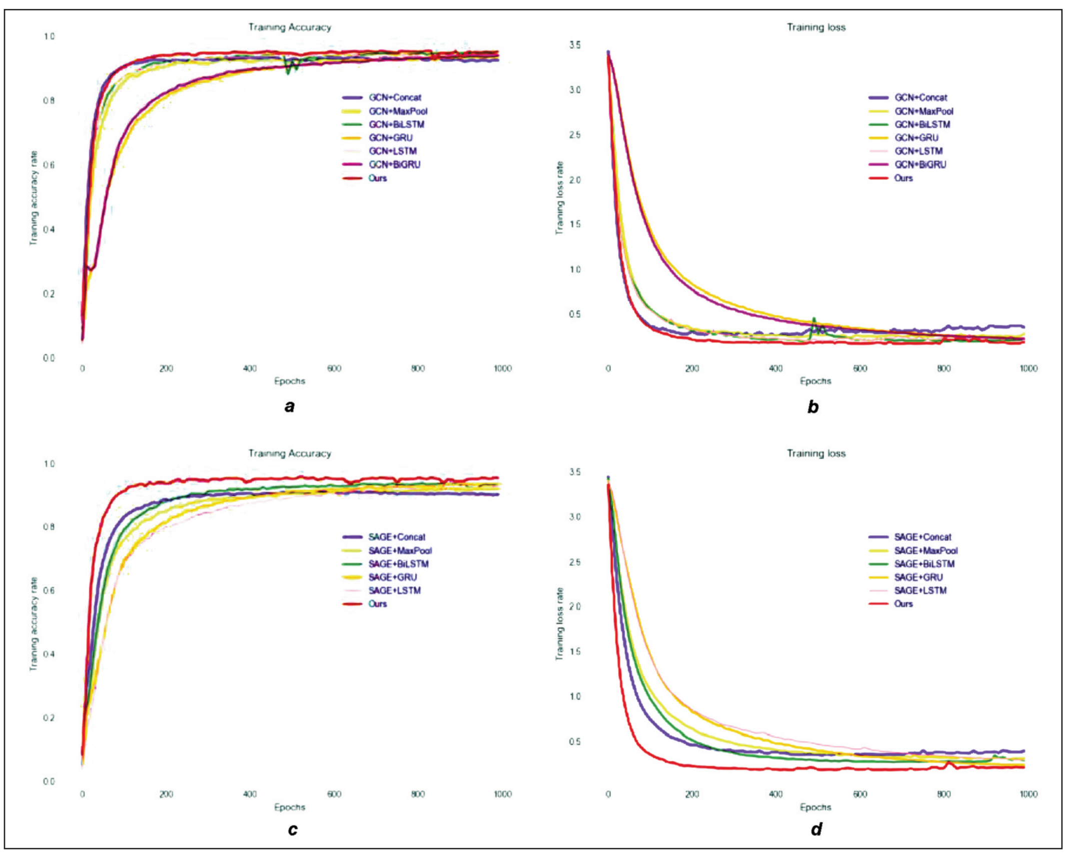

Fig. 4. Comparison of ablation experiment results: *a* – Accuracy(GCN_2+); *b* – Loss(GCN_2+); *c* – Accuracy($SAGE_2$+); *d* – Loss($SAGE_2$+)

DISCUSSION

Researchers suggested methods based on traditional machine learning techniques in previous studies. Table 3 presents a comparison of this work with other baseline approaches.

Table 3

PERFORMANCE COMPARISON AGAINST BASELINE APPROACHES

No.	Details		Accuracy (%)
	Method	Features	
1	Inception V3	Based on surface features	13.1
2	SVM	Based on surface wrinkle	78.3
3	LSTM	Based on video timing	63.8
4	CNN+LSTM [7]	Based on motion video	66.7
5	Regression Model [6]	Based on stiffness and density	70.0
6	GCN_3 [9]	Based on motion video	84.5
7	Ours	Based on motion video	95.9

The above studies were tested in the same public fabric database, which can identify 30 kinds of fabrics. To reflect the advantages of our method, we apply three traditional classification algorithms in machine learning to conduct experiments and synthesize the other three existing study results for comparative analysis. As be analysed that the Inception V3 automatically classified the fabrics with the features of the fabric surface, yet the accuracy of fibre recognition was only 13.1%. The SVM only recognized the wrinkle information on the surface, and the accuracy cannot be strong due to insufficient feature extraction. The LSTM focused on the study of the motion state in datasets, and just considered the inherent timing characteristics, resulting in 63.8%. The Regression Model comprehensively analysed the feature and motion information of the surface for fabric in the video, as well as the CNN+LSTM, used the motion of appearance to infer physical characteristics for textiles, however, the results of the CNN+LSTM and regression model were not very satisfactory, 66.7% and 70.0% respectively. GCN3 and our method comprehensively considered multi-frame timing information and fabric movement characteristics. Compared with GCN_3, the accuracy of our method is about 11.4%, up to 95.9%. In summary, the customized model proposed in this paper had the best effect on the classification of fabrics.

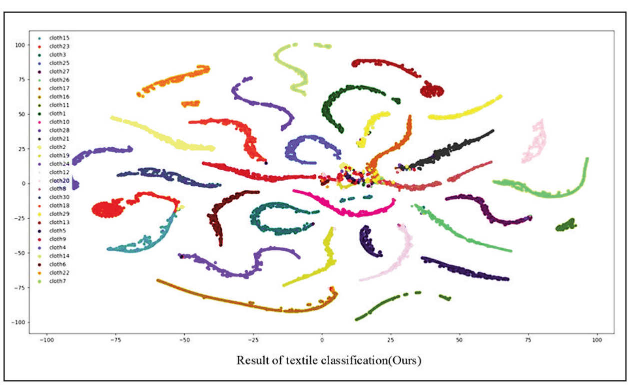

Fig. 5. Visualization of the classification result of 30 textile materials

T-SNE was presented by [31] and is mostly used to visualize high-dimensional data and project it into low-dimensional space. To get the classification recognition effect of our model visually, we visualize the experimental data with T-SNE, as shown in figure 5. It can be observed that a graph node represents a kind of fabric, we attempt to distinguish fabric categories with 30 different colours, and the more nodes of the same colour gather, the better the fabric classification. The node aggregation of the same fabric is obvious except for a very small part.

CONCLUSION

In this paper, we propose a customized graph neural network architecture for the identification and classification of textile material. Our hybrid model takes GraphSAGE to complete the graph embedding operation. and then introduce jump connection and adaptive aggregation mechanism, effectively combining the advantages of BiGRU-attention, thus further improving the model performance. Besides, the model is robust when fabric texture, colour, and other factors are disturbed. In addition, we apply a variety of classification metrics to evaluate the performance of our model. Compared with other baseline methods, the experimental results show that the performance of this method is superior to other existing research, and although there is still upward mobility in our classification effects, it is noteworthy that this work has potential in the textile and fashion industry. In the future, we will further understand the research frontiers of textiles to extract finer fabric features and more accurate motion information to achieve fabric simulation.

ACKNOWLEDGEMENTS

The authors would like to express their gratitude to the team from MIT for providing publicly available datasets of fabric, which supported valuable support for our work. In addition, the authors also will thank the anonymous reviewers for their comments and suggestions.

FUNDING

This work is supported in part by the Science Foundation of Hubei under Grant No.2020BAB116 and Department of Education of the Hubei Province of China under Grant No. Q20131608, and Engineering Research Center of Hubei Province for Clothing Information.

REFERENCES

[1] da Silva BarrosM, A.C., Ohata, E.F., da Silva, S.P.P., et al., *An innovative approach of textile fabrics identification from mobile images using computer vision based on deep transfer learning*, In: 2020 International Joint Conference on Neural Networks (IJCNN), IEEE, 2020, 1–8

[2] Zhan, Z., Li, L., Chen, X., et al., *Discriminative-shared dictionary learning for class-specific fabric texture characterization,* In: Textile Research Journal, 2020, 90, 21–22, 2478–2491

[3] Kim, H.J., Youn, S., Choi, J., et al., *Indexing surface smoothness and fiber softness by sound frequency analysis for textile clustering and classification,* In: Textile Research Journal, 2021, 91, 1–2, 200–218

[4] Han, Y., Liu, C., Wang, Y., et al., *Fabric image classification segmentation based on wavelet transformation coefficient,* In: Journal of Textile Research, 2012

[5] Jing, J., Xu, M., Li, P., et al., *Automatic classification of woven fabric structure based on texture feature and PNN,* In: Fibers and Polymers, 2014, 15, 5, 1092–1098

[6] Bouman, K.L., Xiao, B., Battaglia, P., et al., *Estimating the material properties of fabric from video,* In: Proceedings of the IEEE International Conference on Computer Vision, 2013, 1984–1991

[7] Yang, S., Liang, J., Lin, M.C., *Learning-based cloth material recovery from video,* In: Proceedings of the IEEE International Conference on Computer Vision, 2017, 4383–4393

[8] Bi, W., Jin, P., Nienborg, H., et al., *Estimating mechanical properties of cloth from videos using dense motion trajectories: Human psychophysics and machine learning,* In: Journal of Vision, 2018, 18, 5, 12

[9] Tao, P., Di, P., Junping, L., et al., *Research on Fabric Classification Based on Graph Convolutional Neural Network,* In: Application Research of Computers, 2021, 38, 5, 1–6

[10] Fout, A., Byrd, J., Shariat, B., et al., *Protein interface prediction using graph convolutional networks,* In: Advances in Neural Information Processing Systems, 2017, 30

[11] De Cao, N., Kipf, T., *MolGAN: An implicit generative model for small molecular graphs,* In: arXiv preprint arXiv:1805.11973, 2018

[12] Ji, S., Pan, S., Cambria, E., et al., *A survey on knowledge graphs: Representation, acquisition, and applications,* In: IEEE Transactions on Neural Networks and Learning Systems, 2021

[13] Hamilton, W., Ying, Z., Leskovec, J., *Inductive representation learning on large graphs,* In: Advances in Neural Information Processing Systems, 2017, 30

[14] Kipf, T.N., Welling, M., *Semi-supervised classification with graph convolutional networks,* In: arXiv preprint arXiv:1609.02907, 2016

[15] Battaglia, P., Pascanu, R., Lai, M., et al., *Interaction networks for learning about objects, relations and physics,* In: Advances in Neural Information Processing Systems, 2016, 29

[16] Khalil, E., Dai, H., Zhang, Y., et al., *Learning combinatorial optimization algorithms over graphs,* In: Advances in Neural Information Processing Systems, 2017, 30

[17] Yan, S., Xiong, Y., Lin, D., *Spatial temporal graph convolutional networks for skeleton-based action recognition,* In: hirty-second AAAI conference on Artificial Intelligence, 2018

[18] Krizhevsky, A., Sutskever, I., Hinton, G.E., *Imagenet classification with deep convolutional neural networks,* In: Advances in Neural Information Processing Systems, 2012, 25

[19] Olah, C., *Understanding lstm networks,* 2015

[20] Gori, M., Monfardini, G., Scarselli, F., *A new model for learning in graph domains,* In: Proceedings of 2005 IEEE International Joint Conference on Neural Networks, 2005, 2, 729–734

[21] Scarselli, F., Gori, M., Tsoi, A.C., et al., *The graph neural network model,* In: IEEE Transactions on Neural Networks, 2008, 20, 1, 61–80

[22] Mehran, R., Oyama, A., Shah, M., *Abnormal crowd behavior detection using social force model*, In: 2009 IEEE Conference on Computer Vision and Pattern Recognition, IEEE, 2009, 935–942

[23] David, A., Bouman, K.L., Chen, J.G., Rubinstein, M., et al., *Visual vibrometry: Estimating material properties from small motions in video*, In: IEEE Transactions on Pattern Analysis and Machine Intelligence, 2017, 39, 4, 732–745

[24] Davis, A., Bouman, K.L., Chen, J.G., et al., Visual vibrometry: *Estimating material properties from small motion in video,* In: Proceedings of the IEEE Conference on Computer Vision And Pattern Recognition, 2015, 5335–5343

[25] Bonner, S., Kureshi, I., Brennan, J., et al., *Exploring the semantic content of unsupervised graph embeddings: An empirical study,* In: Data Science and Engineering, 2019, 4, 3, 269–289

[26] Battaglia, P.W., Hamrick, J.B., Bapst, V., et al., *Relational inductive biases, deep learning, and graph networks,* In: arXiv preprint arXiv:1806.01261, 2018

[27] Gilmer, J., Schoenholz, S.S., Riley, P.F., et al., *Neural message passing for quantum chemistry,* In: International Conference on Machine Learning, PMLR, 2017, 1263–1272

[28] Xu, K., Li, C., Tian, Y., et al., *Representation learning on graphs with jumping knowledge networks,* In: International Conference on Machine Learning, PMLR, 2018, 5453–5462

[29] He, K., Zhang, X., Ren, S., et al., *Deep residual learning for image recognition,* In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, 770–778

[30] Sun, J., Yao, M., Xu, B., et al., *Fabric wrinkle characterization and classification using modified wavelet coefficients and support-vector-machine classifiers,* In: Textile Research Journal, 2011, 81, 9, 902–913

[31] Van der Maaten, L., Hinton, G., *Visualizing data using t-SNE,* In: Journal of Machine Learning Research, 2008, 9, 11

Authors:

PENG TAO[1,2], CAO WENLI[3], CHEN JIA[3], LV XINGHANG[3], ZHANG ZILI[3], LIU JUNPING[1,2], HU XINRONG[1,3]

[1]Hubei Provincial Engineering Research Center for Intelligent Textile and Fashion, China

[2]Engineering Research Center of Hubei Province for Clothing Information, China

[3]School of Computer Science and Artificial Intelligence, Wuhan Textile University, China

Corresponding author:

CHEN JIA
e-mail: chenjiawh@sina.com