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Application of Clothing Design Based on Computer Vision Technology Using Hybrid Graph Convolution Neural Network and Lotus Effect Optimization Algorithm



Abstract: - The garment identification problem finds application in both computer vision and deep reading. In academic circles, clothing classification is a topic of great interest. This manuscript proposes an application of clothing design based on computer vision technology using hybrid graph convolution neural network (HGCNN) and lotus effect optimization algorithm (LEA) (ACD-CVT-HGRNN-LEA). Initially, the extracted images from computer vision are collected from Fashion-MNIST dataset. Collected images are pre-processed to improve the quality of cloth design using hybrid graph transformer collaborative filtering (HGTCF). Later, pre-processed images are given to feature extraction; morphological features like shape, structure, colour, pattern, and size are extracted based on proportion-extracting synchrosqueezingchirplet transform (PESCT). Finally, the extracted features are fed to hybrid graph convolution neural network (HGCNN) for effectively classify the cloth design. In general hybrid graph convolution neural network classifier does not express adapting optimization strategies to determine optimal parameters to ensure accurate cloth design detection system. Hence, the proposed method examined utilizing performance metrics like accuracy, precision, F1-score, specificity, Recall, Least square error, and computation timing. Proposed ACD-CVT-HGRNN-LEA method attains 99% higher accuracy, and 150 (s) low times analysed to the existing methods respectively.

Keywords: Transform, Chirplet Extracting, Hybrid Graph Transformer Collaborative Filtering, Cloth Design, Computer Vision.

I. INTRODUCTION

Clothes-related online transactions are growing daily due to the Internet's e-commerce's quick expansion, and this has raised the significance of clothes photos in purchases. But there are many classification standards and a multitude of apparel types [1, 2]. When it comes to more uniform quality, lower costs, and shorter production times overall, manufacturing fills a critical gap that handcrafted or manual production cannot [3, 4]. One aspect of human civilization that has been embodied is dress. Even though people's attire varies over time, the goal of beauty never goes away. Many costume designers may find inspiration in the vibrant sculptures and rich, enchanting depictions of medieval garments preserved in the murals at the Mogao Caves in Dunhuang, which date back thousands of years [5]. These days, computer vision research is mostly focused on the automatic identification of national attire using image recognition technologies [6]. Next, local fine-grained features and a bag-of-words model, like the scale-invariant feature's transform, were used to identify garments belonging to the She nationality that had comparable shapes [7].

The silhouette curve, reference point, and feature size were all calculated using a model that was created to calculate the form ratio and silhouette form value for style identification were used to characterize the garment silhouette information [8, 9]. Unfortunately, the previously suggested techniques perform poorly when it comes to identifying clothing styles with strong silhouette variances and strong similarities [10, 11]. Classification is a possible formulation for the definition problem of the picture of clothing. Machine learning techniques that use different fundamental approaches to garment recognition can be categorized into several groups. Manufactured items are not consistently of a higher quality than mass manufacture [12]. This is especially valid when doing quality checks with human operators since, among other things [13], the production process might not be entirely mechanized due to variables like boredom and exhaustion, which can both contribute to attention gaps that result in the manufacturing of defective products [14].

This work presents a method based on color feature fusion with support vector machines and particle swarm optimization for the recognition of various nationality apparel branches [15, 16]. The general philosophy of Natural Computation, which aims to solve computing issues by drawing inspiration from or adopting methods from nature, is especially compatible with the science of Artificial Intelligence [17]. The growth of electronic commerce has made online clothes purchasing a mainstream way of life [18]. Before submitting the information

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about the clothing to the category, shape, texture, style, cloth, and online shopping mall should all have new labels. The buyer uses keyword retrieval to look for appropriate apparel.

The fundamental purpose of identifying the image which works as a search engine is to return search results without typing. This assists majors in fashion for everyday internet customers who can take images to seek for anything [19].

The main contribution of this manuscript includes;

- This manuscript, ACD-CVT-HGRNN-LEA is proposed. Initially input cloth design is collected from Fashion-MNIST dataset. Afterward, the collected cloth design to pre-processing by utilizing hybrid graph transformer collaborative filtering (HGTCF).
- Following the pre-processing and feature extraction processes, the resulting output is inputted into the classification method.
- The proposed technique is executed and the efficiency of proposed ACD-CVT-HGRNN-LEA art cloth classification is evaluated by several performance metrics like accuracy, precision, F1-score, specificity, Recall, Least square error, and computation timing.
- From the result, it concludes that the proposed approach is better compared with existing approaches like AI-CV-MIH, CIR-MF-DNN and AA-CC-CNN methods respectively.

II. LITERATURE SURVEY

Among the frequent research work on Multi-Feature Based Clothing Image Recognition; some of the latest investigations were assessed in this part.

Shubathra et al. [20] have introduced Clothing image identification was primarily employed in computer vision for fashion applications, catering to an online consumer base. The challenge with fashion items was recognizing their appearance and identifying their style and presentation. With the use of image recognition technologies, customers can instantly navigate to the product page and make a purchase by simply scanning a picture from a print advertisement or fashion magazine. When visual search functions within the application or website, retailers can recommend items that seem identical but are priced differently, allowing the customer to purchase a look-alike product at a reduced cost. Convolutional neural networks, multilayer perceptrons, and extreme learning machines, the primary goal was to classify the MNIST fashion dataset. Deep neural networks, which were extensively utilized for image recognition and much more efficient for evaluating fabric predictions, were used to extract the feminist dataset. Bringing in more youthful female artists, designers, collectors, and students, Fashion-MNIST promotes cultural diversity. A significant obstacle to obtaining high quality accuracy was determining which classification model to use and which deep learning technique was appropriate for feature extraction.

Lai et al. [21] have introduce artificial intelligence and computer vision can boost efficiency and effectiveness in three different areas inside a typical supply chain: producing edible bird's nest, retail e-commerce, and, finally, cancer cell identification.

Su [22] have developed of The volume of clothes purchases made online is growing daily, and with it, so is the significance of clothing photos in these transactions. There numerous classification standards and classifications for apparel, though. A bad online buying experience for clothes can easily result from the difficulty that consumers and e-commerce businesses have in standardizing the description of clothing categories. Clothing classification was made possible using neural networks, which have an excellent list in the computer vision industry. The goal of this paper was to investigate neural network-based algorithm analysis for clothes classification. This paper proposes a multi-task CNN starting with a neural network based apparel picture categorization system. The fundamental framework of the network model remains unchanged when hierarchical categorization data and multitask technology where integrated. It was better for the network to convey sophisticated clothing categories when clothing image classification was accurate. A CNN network and Hu invariant matrix feature fusion was the foundation of the apparel classification algorithm suggested in this paper. To remove the feature with less information gain, the shape feature was utilized to combine the features that the convolutional neural network extracted. The process begins with exploring the feature fusion of the extracted features.

Wu et al. [23] have introduce Cloth-GAN was a cutting-edge method for "designing" new clothes designs and trends. Style transfer algorithms and GANs served as its foundation. In addition, we created the Dunhuang

clothing dataset and ran tests to create new clothing patterns and styles utilizing Dunhuang components. We assessed these ensembles that were fashioned from different models by computing the conception score, the human prefer score, and the generated score.

Ding et al. [24] have introduced while the color qualities of the clothing varied slightly depending on the nationality, there were many shapes and textures that shared similarities. As such, it was challenging to discern the various branches of nationality dress. In order to solve this issue and take color feature fusion into consideration, this work suggests a hybrid PSO-SVM methodology-based recognition tool. The color feature distribution of each branch was obtained by subtracting the color histogram and color moment (CM) feature descriptors from each of the five branches that comprised her nationality garments. Next, dimensionality reduction and optimization of principal components was used to accomplish color feature fusion. To further optimize parameter combinations individually, PSO was introduced. In the end, the several She nationality clothing branches were identified automatically.

Hu et al. [25] have introduced The primary function of dynamic image recognition in today's information technology was to digitize various people's biological data. The recognition function was attained once the distinguishing qualities were compared. The current management method for the clothing sales platform is examined in the first section of this article. Next, the main scenario surrounding AI learning is presented, the sales platform's workflow is analyzed, the needs are looked at, and ultimately, the study centers on whether this technology can enhance the platform. An extensive conversation was started by the company's productivity.

Yu et al. [26] have developed the online clothing shopping Current clothing shopping applications that was popular were recommendations for similar clothes, clothing commodity retrieval, and clothing category labeling. These applications rely on precise clothing picture classification technology. It was very difficult to classify clothes images accurately due to the wide range of designs and variations. The poor classification performance of classic neural networks stems from their inability to extract the spatial structural information present in garment photos. For high accuracy, the spatial structure feature and image feature were used to introduce the upgraded capsule (EnCaps) network. To obtain the structural feature of the garment using the EnCaps network, Initially, the model for extracting spatial structure was introduced. Secondly, an improved feature extraction approach was suggested in order to extract stronger clothing features by utilizing a more profound attention mechanism and network structure.

III. PROPOSED METHODOLOGY

In this section, clothing design based on computer vision technology based on hybrid graph convolution neural network and lotus effect optimization algorithm is proposed. Block diagram of proposed ACD-CVT-HGRNN-LEA is presented in Figure 1. The proposed ACD-CVT-HGRNN-LEA takes the extracted cloth design from the multimedia. This process consists of five steps: pre-processing, feature extraction, categorization, and optimization of the dataset. Accordingly, detailed description of all step given as below,

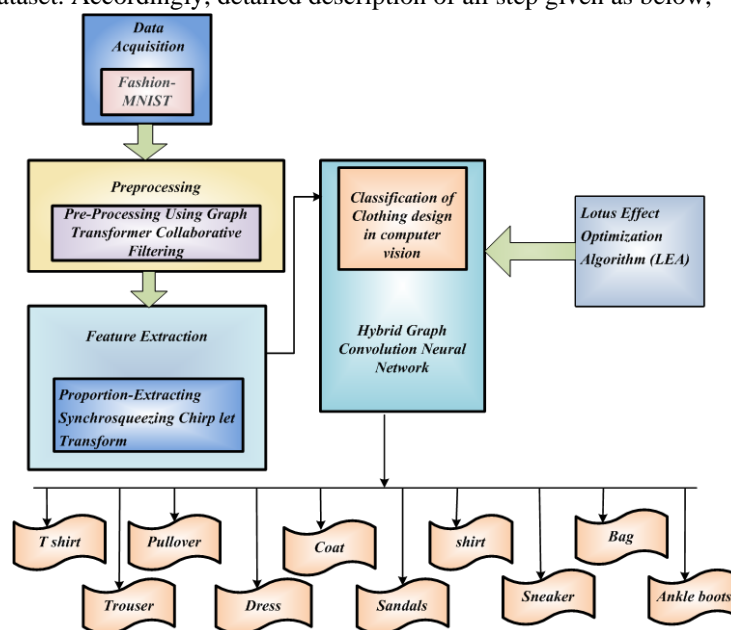


Figure 1: Block diagram for the proposed ACD-CVT-HGRNN-LEA method

A. Data Acquisition

In this study, 70,000 28x28 annotated fashion photographs from an MNIST-like dataset are employed. There are two sets of samples in the Fashion-MNIST dataset of Zalando article pictures: 60,000 samples for training and 10,000 examples for testing. A 28x28 grayscale image is used for each example, designated with a class chosen from ten possible choices. Zalando wants to use Fashion-MNIST for machine learning algorithm benchmarking, essentially replacing the original MNIST dataset with a drop-in alternative. The training and testing splits' picture sizes and structures are the same. The original MNIST dataset includes several handwritten digits. This dataset is well respected by the AI/ML/Data Science community, which utilizes it as a benchmark to verify its techniques. Actually, academics frequently attempt MNIST as their first dataset. "If it doesn't work on MNIST, it won't work at all", they said. "Well, if it does work on MNIST, it may still fail on others." The original MNIST dataset will be replaced by Zalando.

B. Pre-Processing Using Graph Transformer Collaborative Filtering

Image pre-processing is carried out by the GTCF. Our suggestion approach uses graph transformer collaborative filtering to support several behaviors. The dynamic encoding layer and sub-graph generation module are eliminated by GTCF4MB. Examine the behavior graph $G=(V,E,R)$, where V indicates the node set, E signifies the edge set [27], and R is the behavior set. The following is the node representation's information transfer layer:

$$E^{l+1} = \sigma \left(\hat{Q}^{-\frac{1}{2}} \hat{B} \hat{Q}^{-\frac{1}{2}} E^{(l)} Z_r^{(l)} \right) \tag{1}$$

Here $\hat{B} = B + 1$ and $Q = Q + A$. The unit, adjacency, and diagonal node degree matrices are denoted by B, Q and A , respectively. It is employed in the integration of the nodes' self-loop connections. Z_r^l and $E^{(l)}$ stand for the weight matrix of a specific behavior r and layer l , respectively, and $\sigma(\cdot)$ stands for the nonlinear activation function. The aim of the challenge was to create a classification that groups users with comparable tastes together. The graph's structure and ID embedding of every user make up the feature vector, which is shown as follows:

$$F_i = \sigma(Q_1(r_i^{(0)} + r_i^{(1)} + n_1)) \tag{2}$$

Here F_i feature fusion is used to retrieve the user feature the user interface's ID embedding, or $r_i^{(0)}$, is derived from the user representation's initial layer of neighborhoods' interaction graph, or $r_i^{(1)}$. The feature fusion's weight matrix and bias vector are denoted by $Q_1 \in R^{d \times d}$ and $n_1 \in R^{1 \times d}$, respectively. The activation function is σ . The attention weight that item v_j s taught user u_i during behavior r_k , where $!$, is indicated by $h_{i,j,k}$. Similar calculations are made for $h_{j,i,k}$.

$$\omega_{i,j,k}^h = \text{soft max}(\varpi_{i,j,k}^h) = \frac{\exp(\varpi_{i,j,k}^h)}{\sum_{e_{i,j}^k \in E_u} \exp(\varpi_{i,j,k}^h)} \tag{3}$$

Equations show how each layer's embedding representations are merged to get the final demonstrations of the item v_j , user u_i , and behaviour r_k in the prediction layer of this model. The inner product is used to forecast user preferences for products using the learnt embedding of users e_i , objects e_j , and behaviours e_k .

$$y_{i,j}^{(k)} = e_i^T \cdot \text{diag}(e_k) \cdot e_j \tag{4}$$

Where, the diagonal matrix with diagonal elements all equal to e_k is indicated by $\text{diag}(e_k)$. We utilize pairwise loss for learning in order to optimize the model. Specifically, we define the user u_i 's positive interaction terms in S for small batch training. To define the loss function for a sample of both positive and negative events, we do the following:

$$L = \sum_{i=1}^I \sum_{s=1}^S \sum_{k=1}^K \max(0, 1 - y_{i,p_s}^{\wedge(k)} + y_{i,n_s}^{\wedge(k)}) + \lambda \|\Theta\|_F^2 \quad (5)$$

Where, the positive and negative examples are denoted by p_s and ns , respectively. λ and Θ stand for the model's parameters and regularization coefficients, respectively. The technique of L2 regularization is employed to avoid overfitting. In each trial, two standard measures were employed to assess the performance: the normalized discounted cumulative gain and the hit ratio. Top-N recommendation tasks have made extensive use of these two metrics, and recommendation results can be strongly or weakly inferred from HR NDCG ratings. Each positive case was selected with 99 negative examples from the user's non-interactive and interactive objects in order to evaluate the model in an equitable and effective manner. The following is the calculation of *HR* and NDCG.

$$HR @ K = \frac{Hits @ K}{Users} \quad (6)$$

Where *Hits @ K* specifies the quantity of individuals whose test set items are listed in the Top K recommendation list. *Users* represents the total amount of test set users.

C. Proportion-Extracting Synchrosqueezing Chirplet Transform

In this section, feature extraction is discussed. The SSCET is used to extract morphological features like shape, structure, colour, pattern, and size respectively. The typical operating environment of gear boxes is time-varying [28], which results in non-stationary vibration signals. These signals are frequently made up of several time-varying parts that have near-instantaneous frequencies. The first step is to construct the shape of morphological features in cloth design can be expressed as:

$$Shape = [(2i - 1)\mu / 2] \times d_r(\tau) \quad (7)$$

Where *Shape* denotes the initial derivatives in relation to μ , τ regulates the step size to the structure of morphological features in cloth design can be expressed as;

$$Structure = h_s / \{2 \times \max[h_r(t)]\} \quad (8)$$

h_s is the sampling frequency. The colour of morphological features in cloth design can be expressed as:

$$Colour = \sum_{i=1} T_G[t, h; \tilde{d}_i(\tau)].PEO_i(t, h) \quad (9)$$

The constituent components are assumed to be separated in the time-frequency domain by the FSST and WSST in order to produce a concentrated and smear-free TFR. The non-stationary multi component signals with close-spaced IFs, however, are not amenable to high-quality underlying TFRs from the CWT or STFT. Considering the benefits of both the PECT and SST in producing high-resolution underlying TFRs and sharpening underlying TFRs, we adapt the SST to fit the PECT framework and propose the PESCT method. The magnitude of morphological features in fabric design can be described as:

$$Size = \frac{1}{a_\sigma^*(0)} \int T_c(t, h) \delta[h^1 - \hat{h}(t, h)] dh \quad (10)$$

The pattern of morphological features in digital art can be expressed as estimated by;

$$Pattern = \frac{1}{2\pi} \times \frac{\partial \{\arg[T_c(t, h)]\}}{\partial t} \quad (11)$$

Then the extracted features are supplied to the categorization procedure. The procedure for classification is done by hybrid graph convolution neural network. The detail about the classification process is given in the below section.

D. Hybrid Graph Convolution Neural Network

In an edge IoT scenario, a novel convolutional hybrid graph-based neural network for forecasting urban traffic flow is developed by combining graph optimization and prediction into a single pipeline. The original road networks are initially pre-processed for the collection of urban traffic data in order to eliminate noise [29]. To create a GCNN, the first step is to build the adjacency matrix A of the graph: To illustrate, in a non-oriented

network, $A_{ij} = 1$ only in the event that nodes i and j are connected, and $A_{ij} = 0$ only in the event that i and j are not. Furthermore, we build the matrix below after generating the node matrix H :

$$H' = \sigma \begin{pmatrix} \hat{D}^{-1} & \\ & AHW \end{pmatrix} \tag{12}$$

$\hat{A} = A + 1$, W is an indicated node-by-node shared linear transformation that may be learned, σ is representable as a nonlinear function such as ReLU, and \hat{D} is denoted as the degree matrix (\hat{D}^{-1} is present to normalize the adjacency matrix and prevent the features from exploding when they are summed). It is known as the mean-pooling update rule. The following are the outcomes of symmetric normalization:

$$H' = \sigma \begin{pmatrix} \hat{D}^{-1/2} & & \\ & \hat{A} & \\ & & HW \end{pmatrix}, \tag{13}$$

$$\vec{h}_i'' = \alpha \left(\sum_{j \in N_i} \alpha_{ij} W \vec{h}_j'' \right) \tag{14}$$

Where α_{ij} is a coefficient that is either explicitly defined, which results in certain drawbacks, or N_i is denoted as the set of neighbors of node i ,

$$\alpha_{ij} = \frac{\exp(a_{ij})}{\sum_{k \in N_i} \exp(a_{ik})} \tag{15}$$

$$a_{ij} = a(\vec{h}_i', \vec{h}_j', \vec{e}_{ij}) \tag{16}$$

We have shown that a can be learned via a shared self-attention process. Our model employs Graph Convolutional Neural Networks (GCNNs), which are the name of the graph attention network updating rule.

E. Process for Lotus Effect Optimization Algorithm (LEA)

Here, we introduce the Lotus Effect Algorithm, a novel evolutionary algorithm that combines effective operators from the dragonfly algorithm, similar to how dragonflies migrate during flower pollination to facilitate exploration, or how local search and extraction operations can make use of the lotus effect, or the water's ability to clean itself on flower leaves [30]. The paper also highlights how clustering, which improves packet delivery ratio and network lifetime, may be utilized in practice to apply LEA to lower energy usage in Internet of Things nodes. The comprehensive step's technique designated below:

Step 1: Initialization

Initialize population of LEA weight parameter values of generator. It expressed in equation

$$K = \begin{bmatrix} K_{1,1} & K_{1,2} & \cdots & K_{1,L} \\ K_{2,1} & K_{2,2} & \cdots & K_{2,L} \\ \cdots & \cdots & \cdots & \cdots \\ K_{m,1} & K_{m,2} & \cdots & K_{m,L} \end{bmatrix} \tag{17}$$

Here K denotes the LEA population matrix, m is denoted as the number of lotus leaf, L is represent as the number of decision variables, correspondingly.

Step 2: Random Generation

After initialization, input fitness function developed randomness via LEA method.

Step 3: Fitness Function

An initialization value, result is random solution. Assessment of fitness values utilizes outcomes of hyper parameter optimization H' . It expressed in equation (),

$$fitness\ function = Optimizing [H'] \tag{18}$$

Step 4: Exploration Phase

LEA uses behaviour through separation, alignment, and cohesion principles. Cohesion indicates an individual's propensity to be toward the middle of the neighborhood's population. For any swarm, surviving is the primary goal. People must therefore be drawn to food sources and kept away from adversaries. Each of the five parameters that update an individual's location in the swarm when taking into account these two behaviors could be mathematically modeled. Here's how separation is computed:

$$L_j = -\sum_{i=1}^N X_i^t - X_j^t \tag{19}$$

Here N is denoted as the amount of individuals in the neighborhood, X_j^t represents the neighborhood location of individual j in evolution iteration t , and X_i^t shows the location of the current individual in the evolution iteration t , indicated by index i .

$$\Delta K_j^{t+1} = (fL_j^t + bC_j^t + dY_j^t + eE_j^t + hW_j^t) + v\Delta K_j^t \tag{20}$$

Where f represents the coefficient of separation, L_j^t represents the degree of separation of the j person, b is the coefficient of alignment, C_j^t is the j individual's alignment, d is the coefficient of cohesiveness, Y_j^t is the unity inside the j individual, e is the food factor, E_j^t is the j individual's source of nutrition, h is the enemy factor, W_j^t is the enemy of the j individual, w represents the inertia weight, t is the iteration counter, and K_j^t represents the current individual position.

Step 5: Exploitation

The proposed algorithm's extraction step is local pollination. The size of each flower's development region surrounding the best-found flower in this type of pollination is determined by a coefficient. The optimal solution is the starting point for movement, and other solutions gravitate toward it. At the start of the movement algorithm, the steps are taken more slowly, and at the end, they are taken faster.

$$K_j^{t+1} = K_j^t + U(K_j^t - a^*) \tag{21}$$

Where K_{t+1} represent the location of the pollen, U represent the growth area and a^* denotes the best pollen location.

$$U = 2c \left(\frac{4t}{Q} \right)^2 \tag{22}$$

Where Q is denoted as the total number of iterations and t is the algorithm's current evolution iteration.

Step 6: Termination

Check the termination criteria, if it met the condition means optimal solution is obtained, otherwise repeat the process. The hyper parameter is H' from HGCNN is optimized with LEA, for effectively for classify the art images. Figure 2 illustrate the flowchart of LEA.

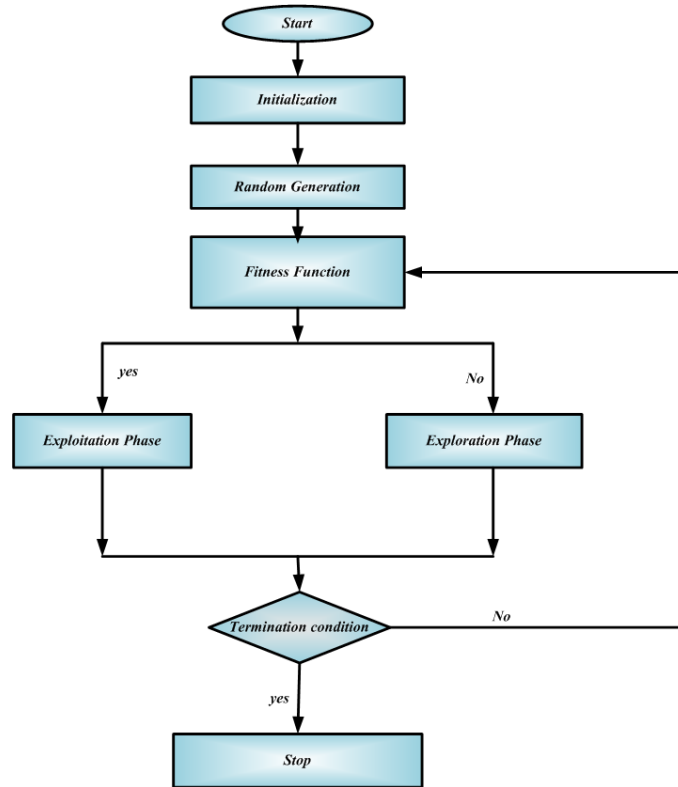


Figure 2: Flowchart of LEA

IV. RESULT AND DISCUSSION

The experimental outcome of proposed method is discussed in this sector. The proposed technique simulated utilizing mat lap based numerous performance measures comprising accuracy, precision, F1-score, specificity, Recall, Least square error, and computation timing. Obtained results of proposed ACD-CVT-HGRNN-LEA method are analysed with existing methods such as CIR-MF-DNN, AI-CV-MIH and AA-CC-CNN correspondingly.

A. Performance measures

This is an important step in selecting the best classifier. In order to assess performance, metrics like accuracy, precision, F1-score, specificity, Recall, Least square error, and computation timing are looked at. It is decided to use the confusion matrix to scale the performance measures.

1) Accuracy

Accuracy is the capacity to measure a value with precision and given in equation (23),

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{23}$$

TP Represent true positive, TN Denotes true negative, FP denotes false positive, FN Represents false negative.

2) Precision (P)

Precision is a metric which quantifies the count of correct positive prediction made. The scale for this is equation (24).

$$Precision = \frac{TP}{(TP + FP)} \tag{24}$$

3) F-Score

A composite measure called F-score which advantages approaches with better sensitivity and difficulties for methods that are more particular, as shown by equation (25),

$$F - score = \frac{TP}{TN + \frac{1}{2}[FN + FP]} \tag{25}$$

4) *Specificity*

The percentage of true negatives that the method correctly identifies is called specificity. It is determined by equation (26),

$$Specificity = \frac{TN}{TN + FP} \tag{26}$$

5) *Error Rate*

This is determined by equation (27),

$$Error\ Rate = 100 - Accuracy \tag{27}$$

B. *Performance Analysis*

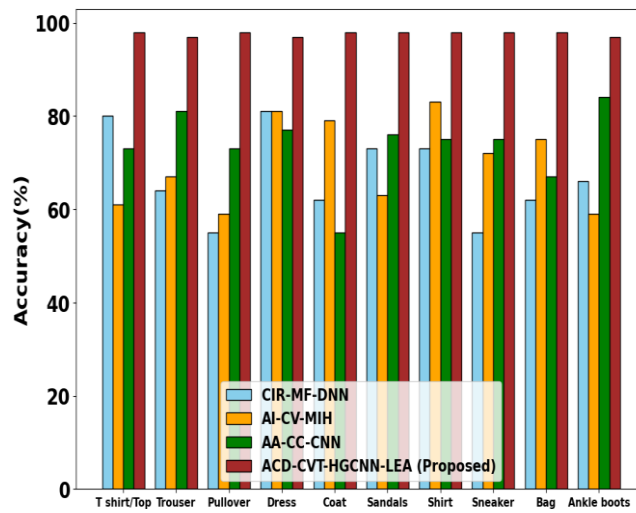


Figure 3: Performance Analysis of Accuracy

Figure 3 demonstrates the performance analysis of accuracy. The proposed ACD-CVT-HGRNN-LEA methods of accuracy are 99% T shirt, 97% trouser, 98.5% pullover, 97% dress, 98.5% coat, 98.5% sandals, 98.5% shirt, 97.5% sneaker, 97% bag, and 95% ankle boots. The existing methods CIR-MF-DNN, AI-CV-MIH and AA-CC-CNN, the accuracy become 80%,60%,72% T shirt, 63%,65%,80% trouser, 55%,78%,72%, pullover, 80%,80%,77% dress, 60%,78%,55% coat, 72%,62%,76% sandals, 72%,82%,75% shirt, 55%,70%,75% sneaker, 60%75%,68% bag, and 65%,60%,86% ankle boots music teaching mode. The proposed ACD-CVT-HGRNN-LEA method shows higher accuracy compare with existing method.

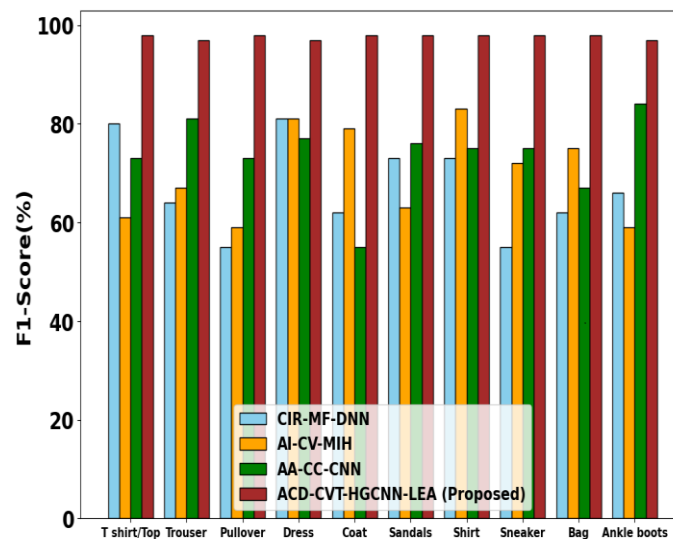


Figure 4: Performance Analysis of F1-Source

Figure 4 demonstrates the performance analysis of F1-Source. The proposed ACD-CVT-HGRNN-LEA methods of accuracy are 99% T shirt, 97% trouser, 98.5% pullover, 97% dress, 98.5% coat, 98.5% sandals, 98.5% shirt, 98.5% sneaker, 98.5% bag, and 96% ankle boots music teaching mode. The existing methods CIR-MF-DNN, AI-CV-MIH and AA-CC-CNN, the accuracy become 80%,60%,72% T shirt, 63%,65%,80% trouser, 55%,78%,72%, pullover, 80%,80%,77% dress, 61%,78%,55% coat, 72%,62%,76% sandals, 72%,82%,75% shirt, 55%,70%,75% sneaker, 61%75%,68% bag, and 65%,60%,86% ankle boots music teaching mode. The proposed ACD-CVT-HGRNN-LEA method shows higher F1-Source compare with existing method.

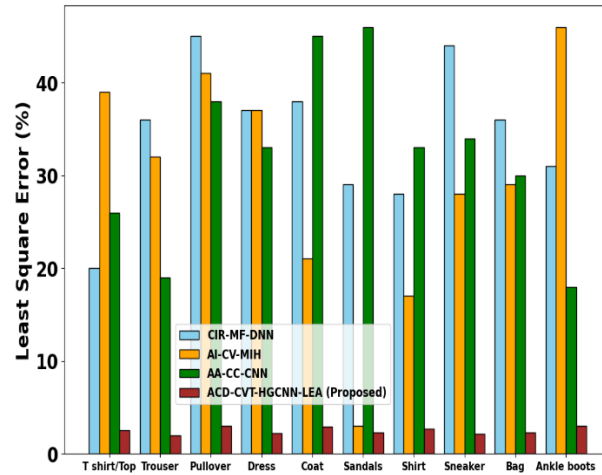


Figure 5: Performance analysis of least square error

Figure 5 demonstrates the performance analysis of least square error. The proposed ACD-CVT-HGRNN-LEA methods of accuracy are 3% T shirt, 2% trouser, 4% pullover, 2% dress, 4% coat, 2% sandals, 3% shirt, 2% sneaker, 2% bag, and 4% ankle boots music teaching mode. The existing methods CIR-MF-DNN, AI-CV-MIH and AA-CC-CNN, the accuracy become 20%,39%,35% T shirt, 36%,33%,19% trouser, 45%,41%,38%, pullover, 37%,37%,34% dress, 38%,21%,45% coat, 28%,4%,47% sandals, 26%,17%,34% shirt, 43%,26%,35% sneaker, 36%,30%,32% bag, and 33%,46%,27% ankle boots music teaching mode. The proposed ACD-CVT-HGRNN-LEA method shows lower least square error compare with existing method.

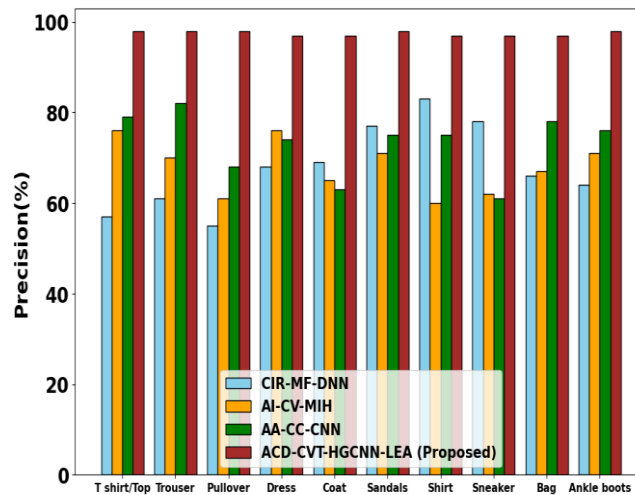


Figure 6: Performance analysis of Precision

Figure 6 demonstrates the performance analysis of Precision. The proposed ACD-CVT-HGRNN-LEA methods of accuracy are 99% T shirt, 99% trouser, 99% pullover, 98% dress, 98% coat, 99% sandals, 98% shirt, 98% sneaker, 98% bag, and 99% ankle boots music teaching mode. The existing methods CIR-MF-DNN, AI-CV-MIH and AA-CC-CNN, the accuracy become 68%,78%,79% T shirt, 60%,70%,81% trouser, 58%,61%,69%, pullover, 70%,77%,76% dress, 70%,65%,62% coat, 80%,74%,76% sandals, 83%,61%,76% shirt, 81%,62%,61% sneaker,67%69%,81% bag, and 65%,74%,80% ankle boots music teaching mode. The proposed ACD-CVT-HGRNN-LEA method shows higher Precision compare with existing method.

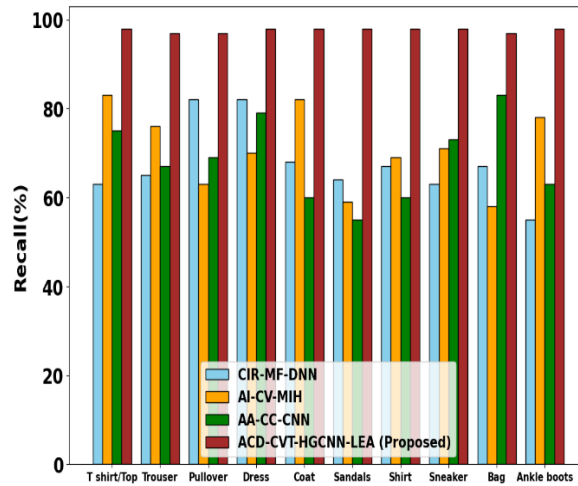


Figure 7: Performance analysis of Recall

Figure 7 demonstrates the performance analysis of Recall. The proposed ACD-CVT-HGRNN-LEA methods of accuracy are 99% T shirt, 98% trouser, 98% pullover, 99% dress, 99% coat, 99% sandals, 99% shirt, 99% sneaker, 98% bag, and 99% ankle boots music teaching mode. The existing methods CIR-MF-DNN, AI-CV-MIH and AA-CC-CNN, the accuracy become 62%, 82%, 77% T shirt, 63%, 74%, 66% trouser, 82%, 62%, 67%, pullover, 82%, 70%, 79% dress, 68%, 80%, 60% coat, 64%, 60%, 58% sandals, 67%, 70%, 60% shirt, 62%, 70%, 72% sneaker, 67%, 59%, 83% bag, and 56%, 78%, 64% ankle boots music teaching mode. The proposed ACD-CVT-HGRNN-LEA method shows higher Recall compare with existing method.

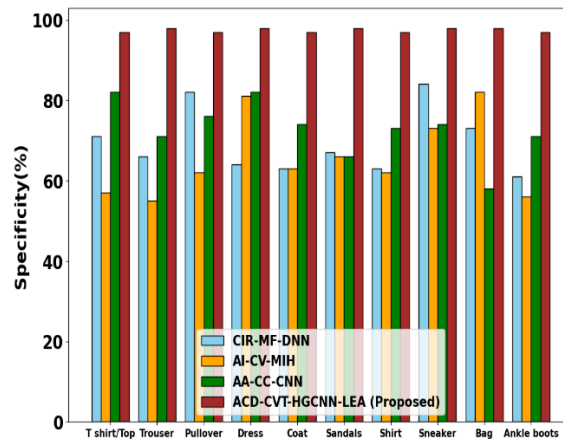


Figure 8: Performance analysis of Specificity

Figure 8 demonstrates the performance analysis of Specificity. The proposed ACD-CVT-HGRNN-LEA methods of accuracy are 98% T shirt, 99% trouser, 98% pullover, 99% dress, 98% coat, 99% sandals, 98% shirt, 99% sneaker, 99% bag, and 98% ankle boots music teaching mode. The existing methods CIR-MF-DNN, AI-CV-MIH and AA-CC-CNN, the accuracy become 70%, 67%, 81% T shirt, 66%, 57%, 70% trouser, 81%, 60%, 76%, pullover, 62%, 80%, 81% dress, 62%, 62%, 73% coat, 67%, 66%, 66% sandals, 83%, 61%, 76% shirt, 81%, 70%, 71% sneaker, 70%, 80%, 60% bag, and 64%, 58%, 69% ankle boots music teaching mode. The proposed ACD-CVT-HGRNN-LEA method shows higher Specificity compare with existing method.

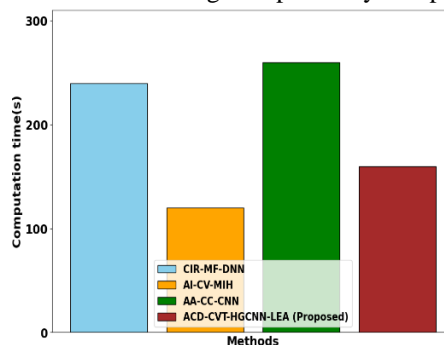


Figure 9: Performance analysis of computation

Figure 9 shown in Performance analysis of computation. The lower computation is occurs at propose method ACD-CVT-HGRNN-LEA which is 150(s) and the higher cost is CIR-MF-DNN method which is 230 (s). At decrease AI-CV-MIH method is 110(s). At increase computation of AA-CC-CNN method is 250(s). Compare to the suggested technique high of computation using the AI-CV-MIH,CIR-MF-DNN and AA-CC-CNN methods. The proposed method ACD-CVT-HGRNN-LEA is minimum value compare with other existing methods.

V. CONCLUSION

In present study, an application of clothing design based on computer vision technology using hybrid graph convolution neural network (HGCNN) and lotus effect optimization algorithm (LEA) (ACD-CVT-HGRNN-LEA). Initially, the extracted images from computer vision are collected from Fashion-MNIST dataset. This paper mainly proposes a method based on the extracted features are fed to hybrid graph convolution neural network (HGCNN) for effectively classify the cloth design.' This paper solves the problem of insufficient research on the classification of existing cloth design, and achieves better classification results of cloth design than existing network models and traditional classification methods. Proposed ACD-CVT-HGRNN-LEA method attains 99% higher accuracy is analysed with existing methods likes AI-CV-MIH,CIR-MF-DNN and AA-CC-CNN methods respectively.

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