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An Efficient Machine Learning based Model for Classification of Wearable Clothing

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Abstract

Computer vision research and its applications in the fashion industry have grown popular due to the rapid growth of information technology. Fashion detection is increasingly popular because most fashion goods need detection before they could be worn. Early detection of the human body component of the input picture is necessary to determine where the garment area is and then synthesize it. For this reason, detection is the starting point for most of the in-depth research. The cloth detection of landmarks is retrieved through many feature items that emphasis on fashionate things. The feature extraction can be done for better accuracy, pose and scale transmission. These convolution filters extract the features through many epochs and max-pooling layers in the neural networks. The optimized classification has been done using SVM in this study, for attaining overall high efficiency. This proposed CNN approach fashionate things prediction is combined with SVM for better classification. Furthermore, the classification error is minimized through the evaluation procedure for obtaining better accuracy. Finally, this research work has attained good accuracy and other performance metrics than the different traditional approaches. The benchmark datasets, current methodologies, and performance comparisons are all reorganized for each piece.

Keywords: Machine learning, back-propagation, classification technique, activation functions, fashion image detection and CNN

1. Introduction

Recently, AI is finding its way into a broad range of businesses as the revolution in computer vision, and artificial intelligence continues from shopping to personal styling and to the design process. Intelligent fashion is a phrase used to describe computer vision-enabled

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fashion technologies. Since fashion items are available in a broad variety of forms and patterns, being fashionable while being educated is tough. Furthermore, the longstanding semantic gap between low-level characteristics and the high-level ideas they express is significant [1-5].

Trends toward digitalization, which is sweeping the business world, do not exclude fashion companies from their operations or their customers. Many new data sources are available to the fashion companies due to the rise of mobile devices, the Internet, social networking services (SNS), and numerous other new technologies that can generate data. These include website click-through rates, browsing histories, and feedback and comments on websites and social media [6]. The fashion business may benefit greatly from this knowledge. Customers' preferences may be used in the development of future items, sales predictions, trend spotting, product ideas, personalized service design, and even in the actual decision-making process itself. Companies must derive meaningful insights from current data and apply these insights to actionable actions to boost competitiveness and prosper in a data-filled world [7-11]. Many factors contribute to the fashion industry's quick evolution, including fast-moving fashion trends and fickle customers. Figure 1 shows the simplified block diagram for predictions.

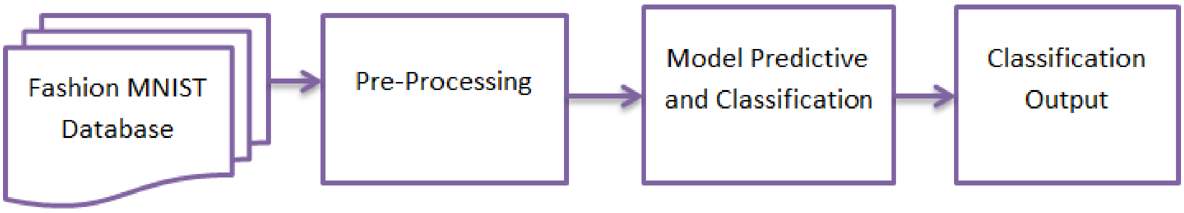

Figure 1. Simplified block diagram for prediction

Analysing data has always been critical to the fashion industry's success. A variety of statistical methods are used for predicting fashion sales, determining garment production decisions, and conducting textile sensory evaluations [12]. These methods are well-known, quick, and valuable for dealing with linear connections between variables. They also work well with organized data. There are currently a variety of data structures available for fashion data, and they may be collected, semi-structured, or unstructured [13].

The fashion items are organized by season, event, weather, and more in a "Created for you" area that consumers may customize with their names and captions. Automatic suppliers, like Style Check, improve incompetence as more photographs, graphics, and criticism are added by the app's users [14].

In addition, Echo Look proposes Amazon products that would be a good match for consumers' existing purchases. Customers may submit images of their current clothing using Echo Look, and Amazon's fashion experts will provide tailored recommendations [15]. This research article contains several sections named related works details, proposed methodology, results description, and conclusion with future possible enhancements.

2. Related Works

As far back as 2014, Liu and his colleagues released a preliminary literature study on intelligent fashion analysis, which included studies on face attractiveness and garment analysis. Since computer vision has advanced so quickly, there are many more areas of intelligent fashion, such as style transfer and physical simulation. Updates are needed on a number of linked tasks [16].

Bringing multimedia to fashion research in 2018, Song and Mei divided activities into three categories: low-level pixel computing, mid-level fashion understanding, and high-level fashion analysis. Human segmentation, landmark identification, and human posture estimation are all examples of low-level pixel processing. A mid-level understanding of fashion seeks to identify photographs of fashion goods and fashion trends. Analysis at a higher level involves suggestions and fashion synthesis, and forecasting fashion trends [17].

An unsupervised transfer learning technique based on part-based alignment and sparse reconstruction was suggested by Liu et al. and is demonstrated from the standpoint of human parsing till garment retrieval. The locality sensitive hashing technique was used to categorize garment segments based on the prior probability map of the human body generated by pose estimation. To identify visually comparable objects, the overlap similarities were totaled. These are notable for their reliance on hand-made elements [18].

Using two copies of the Inception-6 network with shared weights, Wang et al. constructed a Siamese network. They employed a multi-task nuanced tuning technique to include a robust contrastive loss to relieve over-fitting caused by visually distinct positive pairings, and they developed a better feature representation by adjusting the parameters of the Siamese network using photos from ImageNet [19].

Huang et al. constructed the Dual Attribute Aware Ranking Network (DARN) using attribute-guided learning. The DARN models the disparity across domains by concurrently including semantic characteristics and visual similarity restrictions into the feature learning step [20]. Li et al. could get the total query clothing item using sparse coding and a hierarchical super-pixel fusion technique. It was possible to find comparable photos in the product apparel dataset using an over-segmentation hierarchical fusion approach with human posture estimation [21].

A global-local embedding module for improved landmark prediction performance was also suggested by Lee et al. who took into account clothing context [22]. Many research articles presented a wide-ranging benchmark called Deepfashion2 for four tasks: garment identification, posture estimation; human segmentation; and clothing retrieval. They created a robust Match R-CNN model based on a Mask R-CNN for each of the four tasks.

2.1 Problem statement

However, according to the literature review, there seems to be a lack of specificity about how the fashion experts help with Style Check. It is challenging to analyze semi-structured and unstructured data using traditional methods. Due to the inability of standard instruments to deal with complicated nonlinearity among various variables, vital information is lost.

3. Methodologies

In the Machine Learning field, Neural Networks (NNs) and machine learning in particular, have been more popular in recent years. That comes as no surprise considering that Neural Nets are responsible for the majority of the most recent state-of-the-art outcomes on different Machine Learning challenges.

3.1 Design of Neural Network

The classifiers may be as simple as a single neuron, but the complexity arises when layering them. Data are sent between layers of neurons, which are linked in an acyclic network. The three layers of this neural network are the input, the hidden, and the output. If the input data are large enough, three neurons are used in the input layer. During the training method, the model is supplied by four neurons, each with four weights. The prediction made by this study is that it can be provided by two neurons in its output layer [23-28]. Figure 2 shows the block diagram of proposed framework for classification of fashion items.

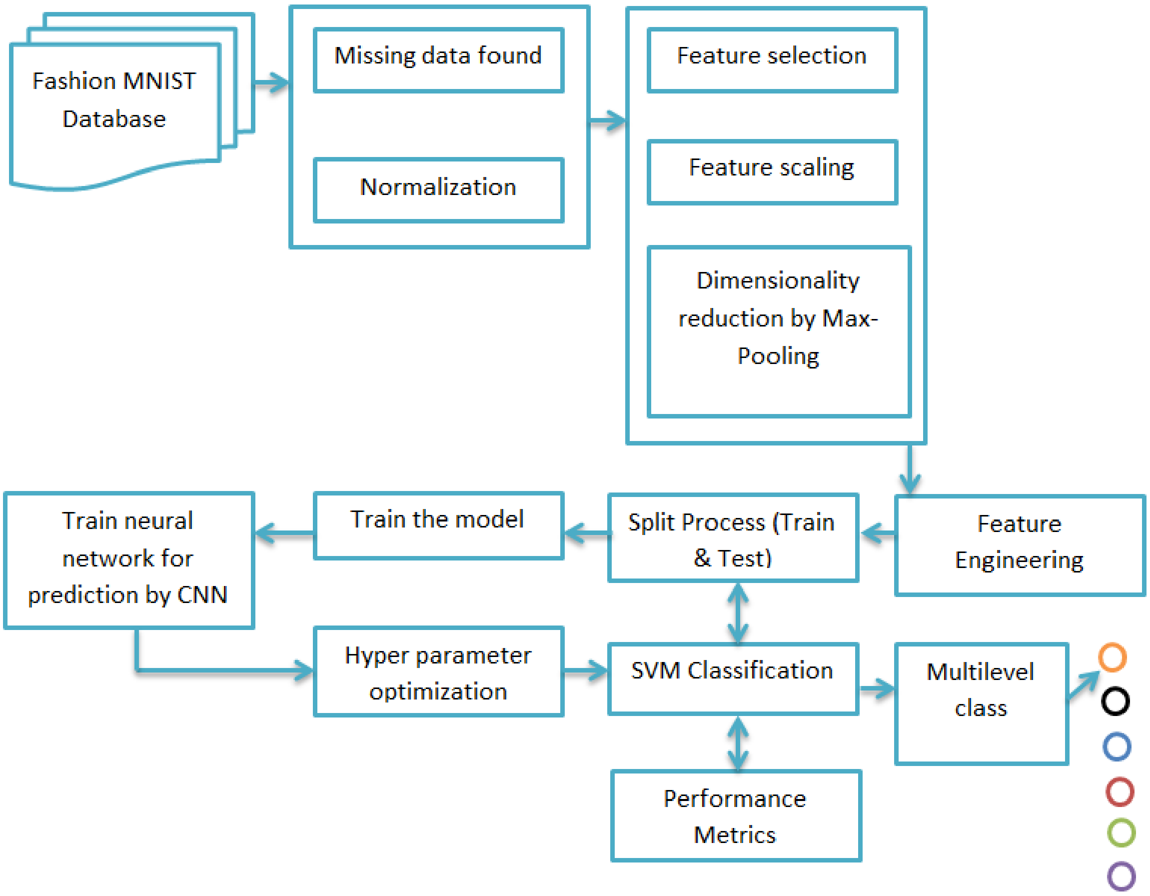

Figure 2. Proposed framework for classification of fashionate things

Until recently, the sigmoid function was a popular activation function. Every real input value is a differentiable function between 00 and 11; it has a characteristic S form. At each point, the derivative is in the positive range. This activation function will activate the model's hidden layer.

3.2 Back-Propagation

Almost everything accomplished with neural networks rely on back-propagation. Therefore, subtasks in the algorithm are broken down into three:

1. Forward bias conditions
2. Error Manipulation
3. Back-propagation

The data and network weights are used by the background to predict the first phase. Next, the forecast and the labels are used to determine the error. Lastly, the mistake is spread across the network, beginning at the very bottom [29]. As a result, the weights are adjusted incrementally depending on inaccuracy.

3.2.1 Train the Neural Networks

Using the background algorithm, each epoch evaluates the weights' errors and gradients. As the last step, the consequences are updated by adjusting the learning rate and angle. The XOR logic is a little more sophisticated when it comes to creating a background. Prior to delivering the gradients for L1 and L2 regularization, it makes a further attempt. Regularization is a technique for guiding the training towards simpler approaches by punishing big values of the parameters.

3.2.2 Weight vector Initialization

The uniform distribution is, performing with the values from -1 to +1 for the weights updating procedure.

3.3 Accurate Image Classification

As a machine learning algorithm, the Support Vector Machine (SVM) works well for both classification and regression tasks. However, categorization is the most common usage of it. There are n-dimensional dimensions in this SVM technique, and each feature is represented by a specific coordinate. Next, the classification is done by selecting the hyper-plane that best distinguishes the two classes [30]. SVM has gamma, C, and kernel, which are the most important parameters. Gamma functions are defined as the extent to which a single training sample may impact the outcomes. Small and large deviations in computation costs are controlled by the C. For this SVM algorithm's kernel, mathematical functions are used. Polynomial as well as linear are examples of this [31].

3.4 Evaluation Procedure

3.4.1 Error Measurement

At this point, the dot product between the data X and the weight vector hidden is considered, activation function is applied, and the output of the hidden layer is obtained. The predictions are then obtained by multiplying the result of the hidden layer by the weight vector output. The difference between the expected and actual numbers is used to determine the error. There are certain caveats to the method used here. Following that, the weights are modified in accordance with the results of the computation [32]. Note that the weight vector output and the first derivative using sigmoid prime are dependent on the outcomes of the forward pass of hidden. The cross entropy loss is also referred as log loss function. To determine the error, the cross-entropy loss (also known as log loss) function is used. Classification models that provide probabilities are evaluated using this function.

$$cross\ entropy = -\sum_{c=1}^{C} y_{0,c}\ \log(P_0, c)$$

There are C classes, y is a binary indication indicating that the class label is valid, and p is the anticipated probability that the observation is in class C. Mean error is determined by calculating the cross-entropy loss and then by adding regularization factors. Here is the implementation of L1 and L2 regularizations.

3.4.2 Predication Evaluation

Neural network predictions are made by taking a step forward from the data. However, the ultimate result is a vector of numbers indicating how confident each class is in the data. Then, using MLE (Maximum Likelihood Estimation), the final predictions are calculated. It's possible to get a probability distribution for all types, using the prediction probability approach. The softmax function is applied to the result of the forward step.

4. Results and Discussion

The Fashion Landmark Dataset is the most frequently used benchmark dataset for fashion landmark identification. However, significant differences exist between these two sets of data:

1. Image normalization for standardization process
2. Multi scale variation

The Fashion-MNIST dataset of various images contains 56k training examples and 12k test measurements. A 28x28 grayscale picture is connected with a label from one of ten classes. For the purpose of evaluating machine learning methods, Fashion-MNIST is intended to replace the original MNIST dataset. It is obvious how the training and testing portions differ in picture size and structure. The dataset is split by training and testing at 80% and 20%, respectively. The following formulas are used to measure the performance of hybrid proposed algorithm.

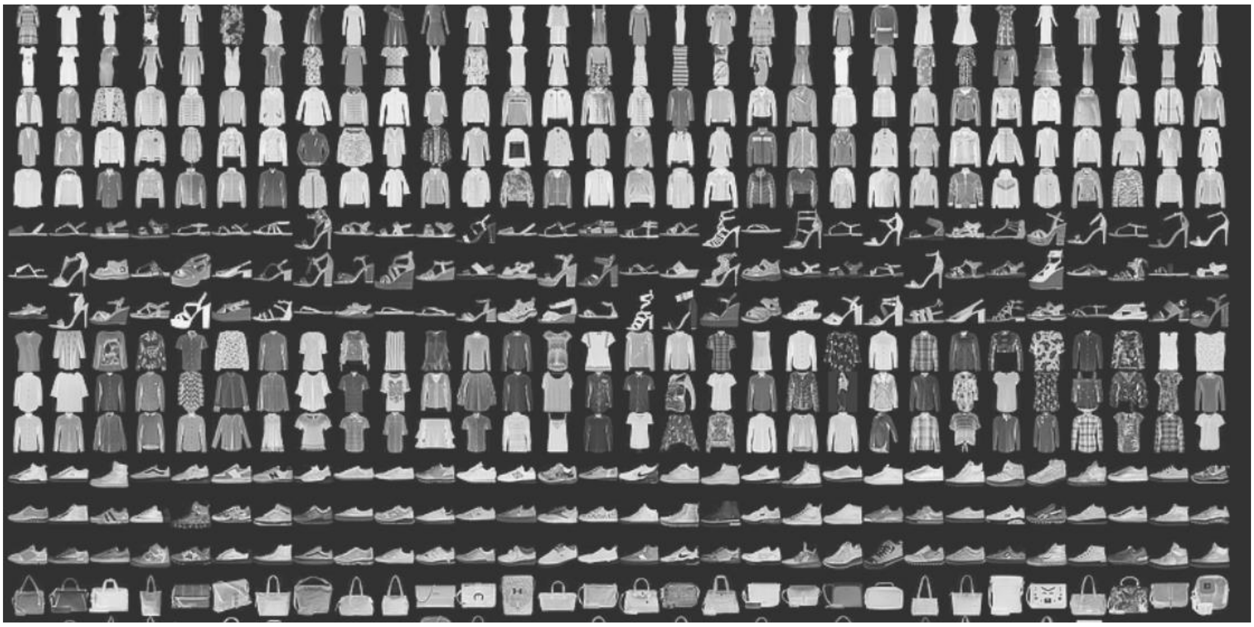

Figure 3. Benchmark fashion-MNIST dataset [34]

Figure 4. Sample obtained predicted images for classification

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ score = \frac{2 * (precision * Recall)}{precision + recall}$$

Figure 4 shows some sample obtained predicted and classified images by this proposed hybrid algorithm. Any machine learning model that aspires to high efficiency will need an increased accuracy. Sadly, it doesn't seem that this model can reduce the inaccuracy by 75 to 150 epochs or more. While a random proposed classifier may provide anywhere from 10% to 50% accuracy on the test dataset, it may not a helpful classifier for practical use [33]. Because of this "jagged" training error line, this model cannot be converted. Instead, this suggested model is trained with the back-propagation technique. Using normalized data, speeds up the connections between neural networks that have been introduced.

The proposed hybrid method classifies the sample predicted pictures in the dataset using a multiclass classification scheme. Consequently, the prediction accuracy of CNN is sufficient, and SVM's classification is a hybrid approach. As indicated in Table 1, the suggested hybrid system performs well, as shown by the results.

Table 1. Computed performance metrics for various model

Method	**Accuracy**	**Precision**	**F1 score**	**Sensitivity**	**Specificity**	**Overall efficiency**
SVM (Prediction and Classification)	85%	79.76%	82.1%	83.96%	77.87%	Low
CNN model (predication and classification)	90%	88.67%	87%	89.45%	90.91%	Medium
Proposed Hybrid Model	98.82%	97%	94.23%	90.78%	93.23%	Very High

The graphical depiction demonstrates that the proposed hybrid method performs much better than previous single classifier algorithms. Figure 5 shows the graphical representation of the performance measures of different algorithms.

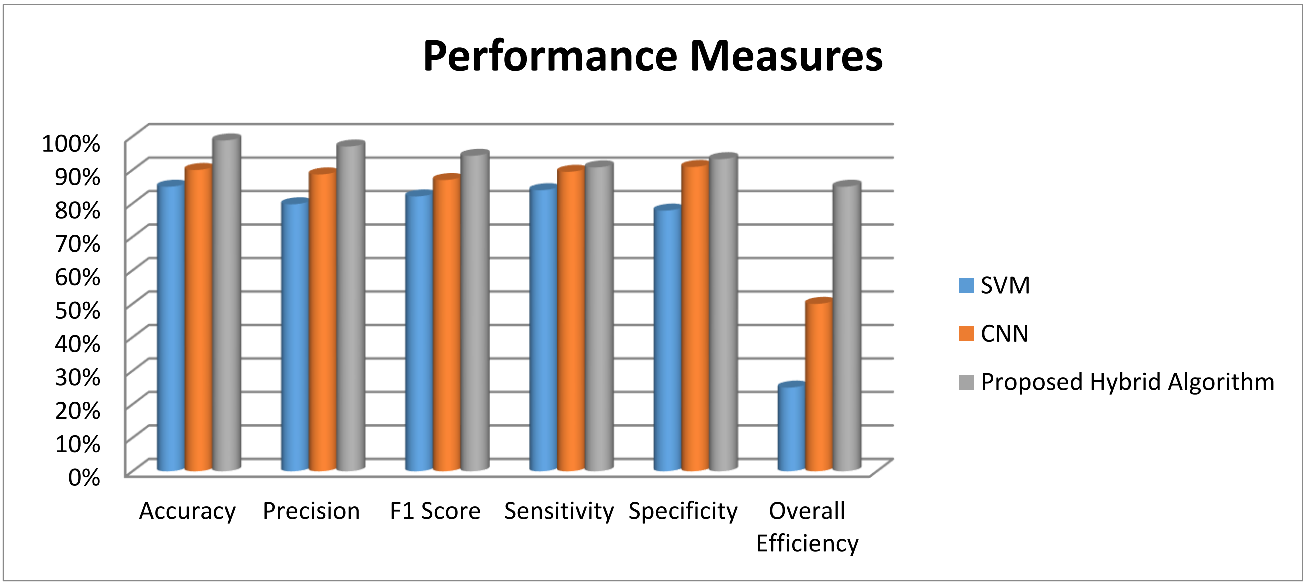

Figure 5. Graphical representation of performance measures

5. Conclusion

Thus, the wealth of data provided by social media and e-commerce websites, may be mined for insights that might help fashion designers create more sophisticated strategies. Based on the abovementioned discussion, fashion technology has been presented to deal with picture identification, analysis, synthesis, and other fashion-related challenges. This proposed combination of CNN and SVM performs better in classifying fashion items than other traditional methods which is shown in the figures and the table in previous section. A systematic and thorough assessment is currently lacking to create a complete picture of intelligent fashion, review and categorize current approaches, examine datasets and evaluation criteria, and provide insight into potential new areas of research to pursue. In the next few years, the researchers need to concentrate on acquiring more sales data. Artificial Neural Network and deep learning, which now perform effectively, could be improved for fashion forecasts in the future research. Depending on how many people click on a product or how much money a product will bring in, regression models may be used instead of categorization.

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