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REVIEW ARTICLE

Artificial Intelligence (AI)-Driven Business Intelligence for Enhancing Retail Performance with Customer Insights

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ABSTRACT

The primary goal of a retail company's business intelligence (BI) deployment is to examine the advantages of BI adoption as well as the challenges that arise. The research is on a big-box retailer that sells a variety of goods and has operations in several nations. Online fashion retail has seen rapid growth, necessitating efficient and accurate clothing classification for improved customer experience. This research introduces a method for classifying garments using a tagged dataset of purchase data that relies on convolutional neural networks (CNNs). A CNN model is trained using a SoftMax layer for classification after convolutional and pooling layers for feature extraction. The dataset is divided 80:20 between testing and training. In terms of accuracy (94.6%), precision (96.8%), recall (96.8%), and F1-score performance, the CNN model performs better than benchmark models such as InceptionV3. The suggested model's ability to increase classification accuracy for online fashion retail applications is validated by the comparison study. Through improved product categorization and user experience, this research demonstrates the potential of deep learning models to improve the classification of clothes sold online.

Key words: Artificial intelligence, Business intelligence, Clothing data, Fashion industry, Machine learning, Online retailing, Retail landscape

INTRODUCTION

The retail landscape has undergone a profound transformation, influenced by evolving consumer expectations, rapid technological advancements, and the increasing dominance of digital platforms. Companies are realizing that in order to stay ahead of the competition, they need to optimize their operations and provide better consumer experiences by utilizing data-driven insights.[1,2] Among various retail sectors, the fashion industry stands out as one of the most dynamic and fast paced, characterized by ever-changing trends, seasonal demand fluctuations, and shifting consumer preferences.

Retail, as a whole, has seen a significant shift towards digitalization, with online retailing emerging as a dominant force.[3,4] With the growing preference, customers may now purchase a variety of goods, have easy shopping experiences, and receive tailored suggestions thanks to e-commerce.[5] In the fashion industry, online clothing retail has seen unprecedented growth, fueled by mobile commerce, social media marketing, and flexible return policies.[6] However, while online retailing offers numerous advantages, it also introduces challenges such as high return rates, complex inventory management, and fluctuating consumer demand, which can negatively impact profitability and operational efficiency.

Businesses are using machine learning (ML) and artificial intelligence (AI)-powered predictive analytics to address these issues. Retailers can now analyze enormous volumes of data to spot trends in customer behavior, predict changes in demand, and improve stock management, thanks to these technologies.[7] Business intelligence (BI) solutions powered by AI improve decision-making by combining market trends, client preferences, and previous sales data to produce useful insights.[8,9] By leveraging AI-driven predictive models, fashion retailers can streamline supply chains, personalize marketing campaigns, and reduce return rates by better understanding purchase behaviors and preferences. The incorporation of AI and ML into BI frameworks is transforming retail strategy by enabling companies to actively influence market trends rather than just responding to them.[10]

Fashion retailers can keep a competitive edge in the digital market by utilizing predictive analytics to build smarter, more adaptable retail ecosystems that meet the changing demands of contemporary customers.

Motivation and Contribution of Paper

The growing demand for precise and effective deep learning (DL) models to improve predicted performance in challenging categorization tasks is what inspired this study. Convolutional neural networks (CNNs) are perfect for processing high-dimensional data because of their remarkable feature extraction and pattern recognition capabilities. This work attempts to enhance model generalization and resilience by fine-tuning hyperparameters and utilizing cutting-edge methods, including dropout, batch normalization, and adaptive learning rates. The results aid in the creation of AI-powered solutions that improve decision-making across a range of industries, such as cybersecurity, healthcare, and finance. The main contributions are:

- Collected a high-quality clothing dataset from reliable sources to ensure data integrity and relevance
- Implementing image resizing, background elimination, and data augmentation to refine model input and improve classification performance
- Improve the CNN model's performance to extract the desired characteristics
- Designed a CNN model with fine-tuned hyperparameters to enhance classification accuracy and generalization
- To achieve the best and most balanced classification result, models are evaluated using the F1-score, recall, accuracy, precision, recognition, and loss functions
- Compared the CNN model that has been suggested with traditional ML approaches to highlight performance improvements.

Novelty and Justification

This work is innovative because it uses a thorough approach to data collecting, guaranteeing balanced and high-quality samples for better model training and generalization. By incorporating advanced preprocessing techniques such as image resizing and data supplementation, the research strengthens the CNN model's resilience. In addition, the integration of EDA helps uncover hidden patterns and biases, optimizing the dataset for DL applications. The justification for this approach stems from the need for reliable, high-performance AI models, where Accuracy and practical application are greatly impacted by the caliber and variety of training data.

Structure of the Paper

The study is structured as follows: Relevant research on internet retailing in the industry is presented in Section II. The methods, materials, and processes are described in depth in Section III. An analysis and presentation of the experimental results are made available in Section IV, along with a description of the suggested system. It concludes with a presentation of future research in Section V.

LITERATURE REVIEW

The literature study on BI for retail performance with consumer insights using ML and DL techniques is covered in this Section. Table 1 below summarizes the summary of the review's methodology, datasets, main conclusions, restrictions, and next steps.

Alfian *et al*. multilayer perceptron, ADASYN data balancing, and iForest Outlier Detection are suggested to be integrated. The proposed model outperformed prior supervised learning models, according to the results, with gains of up to 97.750% in 98.333% specificity, 98.0008% accuracy, 98.333% recall, and 98.778% F1-score. Finally, they demonstrated how to integrate this trained model into an online application. In addition to helping with product positioning, promotions, and customer suggestions, this outcome can help managers better understand client preferences.[11]

Wen *et al*. developed an ML model, multi-behavioral trendiness-product popularity (MBT-POP), that analyses 445,336 sessions, including 33,339,730 clicks from actual e-commerce consumers, to forecast their purchasing behavior using MBT and POP. The result of the data shows how well the MBT-POP model predicts the purchase behavior of anonymous clients with F1 value equal to 0.9031 and the best prediction within a 2-day sliding window of prediction. POP and trendiness, according to the current research,

Table 1: Summary of literature review on business intelligence for online retailing using machine learning

Author	Methodology	Dataset	Key findings	Limitations/future work
Alfian *et al*.	Data balancing using ADASYN, multilayer perceptron (MLP), and iForest outlier detection	Stock data	The results showed 97.750% F1 score, 97.778% accuracy, 98.008% precision, 98.333% specificity and 98.333% recall. Incorporated into a management decision-making online application	Further improvements in model generalizability and real-time application
Wen *et al*.	MBT-POP model (multi-behavioral trendiness and product popularity)	3,339,730 clicks from 4,45,336 sessions of actual online shoppers	I got an F1-score of 0.9031. Successful in using a 2-day sliding window to forecast anonymous consumer purchases	Further validation across different e-commerce platforms
Lumoring *et al*.	Learning algorithms for stock market forecasting (SVM and LSTM)	Stock market data	Among the models tested, LSTM had the best performance in forecasting stock prices (99.58%)	Future research ought to examine real-time market situations and hybrid models
Khatri and Rungi	Logistic regression for predicting product returns	3,187 past orders from an Indian e-commerce company	The model reduced return-associated expenses by 17% and accurately forecasted 60% of product returns, achieving a total efficiency of 87%	Need for expansion to other e-commerce sectors and testing on larger datasets
Eheliyagoda *et al*.	Decision support system using LSTM, ARIMA, regression, classification, and association rule mining	Customer, supplier, pricing, and employee performance datasets	Managed relationships with customers and suppliers, estimated prices and demand, and monitored employees with an accuracy rate of over 90%	Further refinement of predictive models and integration with real-time data sources

may greatly enhance the customer buy behavior model's prediction performance and be crucial in forecasting the purchasing patterns of anonymous consumers.[12]

Lumoring, *et al*., intends to identify the most popular ML models or techniques for market prediction and to give a summary of ML applications in the stock market. However, with an astounding accuracy rate of 99.58%, long short-term memory (LSTM) is the ML approach with the highest level of accuracy.[13]

Khatri and Rungi is an Indian e-commerce firm that, as an example, has product returns of about 25%. The dependent variable, product returns, is dichotomous, and its prediction was based on logistic regression. They suggested a decision-support system that uses the variables and a machine-learning strategy. The model was trained using 3,187 previous orders and then tested for 1 month in a trial program. The model achieved an overall efficiency of 87% and was able to accurately forecast 60% of product returns. By basing initial judgments on these forecasts, the case company was able to avoid spending 17% on product returns.[14]

Eheliyagoda *et al*. have four essential elements, serving as a remedy for the mentioned deficiencies. Major ML components of this decision-support system included LSTM and ARIMA models, as well as regression, classification, and associate rule mining algorithms. The final platform achieved a performance level of more than 90% in all four main areas when tested with the specified datasets.[15]

Table 1 summarizes key studies on BI for online retailing using ML, highlighting methodologies, datasets, findings, and future directions, emphasizing accuracy, predictive performance, and real-time applicability improvements.

METHODOLOGY

As seen in Figure 1, the suggested approach for online fashion shopping starts with obtaining the clothes dataset, which includes transaction data that has been labeled. The preparation of the clothing data includes reducing the image to 224 × 224 pixels, removing the backdrop to make the model more durable, utilizing data augmentation techniques such as flipping and rotating, and applying algorithms such as Grab Cut and Otsu's thresholding. After that, the dataset is divided in half, with 80% used for testing and 20% for training. After convolutional and pooling layers have extracted features, a fully connected SoftMax layer in a CNN model used for classification produces the final predictions. The model is evaluated using different measures such as recall, accuracy, precision, F1-Score, and loss. Finally, confusion matrices and accuracy/loss curve are employed to analyze the performance and it is compared with the existing models.

Briefly described below are the steps of the flowchart as follows:

Data Collection

This study's clothes dataset is crucial since it forms the basis for building and testing algorithms for clothing identification and classification tasks. Shirts, pants, dresses, shoes, and accessories are all part of this dataset, which represents a wide range of colors, patterns, and designs seen in actual fashion. Because of the diversity and size of the dataset, their models are able to understand strong and unique properties, which greatly improves their accuracy when it comes to clothing item classification. The following are some examples of the dataset's images:
Figure 2 presents a diverse set of clothing items from a fashion dataset. There are many different types of clothing in the dataset, including shoes (slippers, sandals), tops (shirts, T-shirts, jackets), bottoms (denim, shorts, skirts), and even gowns and blazers.

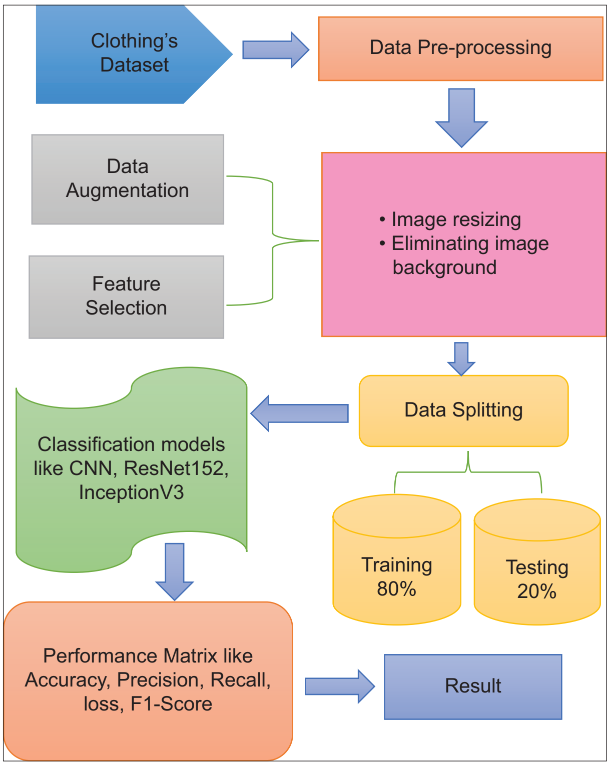

Figure 1: Flowchart for online fashion retailing

Data Pre-processing

A technique called data preparation needs to be carried out to prepare raw data for an ML model. In this paper, Images are resized, and the photographs are made better using data augmentation methods and removing backgrounds. Listed below are the pre-processing steps:

- Image resizing: The input requirements of the models and the photographs' sizes are met by scaling them to 224 × 224 pixels, which also ensures alignment and consistency. The images are then rotated 90° and flipped horizontally and vertically.
- Eliminating image background: The grab cut algorithm is used to eliminate background noise, isolating the clothing items to focus on relevant features. The background elimination is shown below:

Figure 3 illustrates the process of extracting clothing from an image using the grab-cut algorithm and Otsu's thresholding. The original image from a clothing dataset undergoes preprocessing, including hue image conversion and Otsu thresholding to create a binary segmentation. A mask is generated to separate the foreground (clothing) from the background. The filled image is obtained by converting white regions to black, and refining the segmentation. Finally, the extracted cloth is obtained, effectively isolating the clothing from background noise.

Data Augmentation

A helpful method for expanding the training dataset's size is data augmentation, which involves making different adjustments to the current data.[16] A lot of the methods used to enhance time series data, such as cropping, inverting, and adding noise, originated from methods used to enhance picture data.

Figure 2: Clothing products of dataset

Techniques for data augmentation applied to pictures from the apparel dataset are shown in Figure 4. The left section presents the original apparel images with their respective dimensions (533 × 400 pixels). As part of preprocessing, the images 224 × 224 pixels are the typical dimension to which they are resized. Techniques for augmenting data, include 90° rotation and vertical/horizontal flipping, increase model resilience through the introduction of variability, enhancement of generalization, and reduction of overfitting. These are crucial for DL-based fashion classification to boost performance across apparel categories.

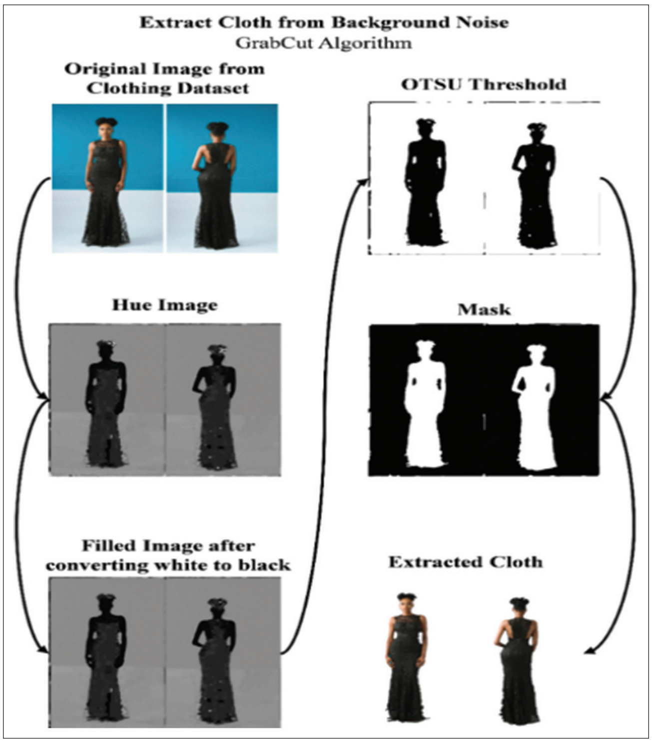

Figure 3: Eliminating image background

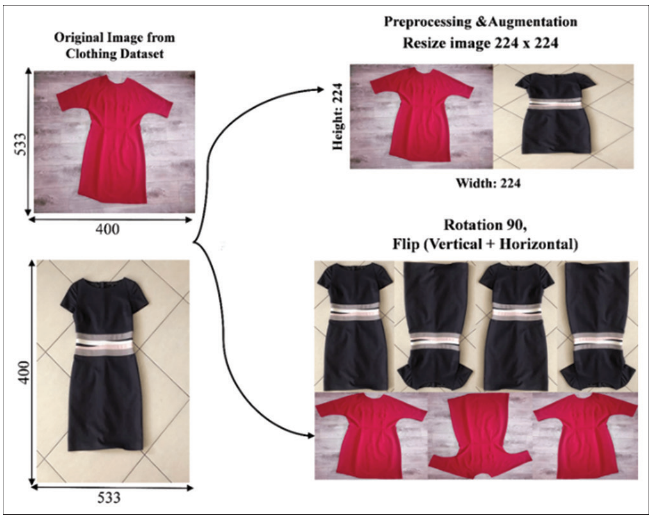

Figure 4: Augmented images of dataset

Feature Extraction

Feature extraction in this study is achieved through DL-based techniques using CNNs.[17] The model automatically learns hierarchical feature representations from clothing images, capturing edges, textures, shapes, patterns, and colors at different levels. Following their retrieval, the feature maps are normalized and put into fully connected layers for the classification procedure.

Data Splitting

The pre-processed data are used to produce a set for testing and another for training. After the model is trained using the testing set, which makes up 20% of the total, its performance is evaluated using the training set, which makes up 80%.

Classification with CNN

CNNs are regarded as DL's foundational architecture. A pooling layer and one or more consecutive convolution layers make up the CNN architecture.[18,19] A completely linked layer and a classification layer, respectively, are added to these layers. The CNN model that Kim suggested was used in this investigation. This model's architecture is a minor modification of Colbert's CNN design. These characteristics are used in the CNN architecture to categories input data.[18,20] There are n inputs in the input layer, and each one is represented by a dense vector with k dimensions. Thus, a $d \times k$-dimensional feature map denotes the input x. Let $xi \in Rk$. In the input sentence, the itch word is represented as k-dimensional word vector. Equation (1) represents an n-length phrase.

$$x_1{:}n = x_1 + x_2 + \ + x_n \tag{1}$$

In this case, the concatenation operator is ⊕. A convolution operation applies the $w \in Rhk$ filter over A new feature can be created using a window of h words. For instance, the following is the generation of a new property c_i feature using a window of x_i: it_{h-1} words in Equation (2).

$$c_i = \mathrm{f}(w\, x_i{:}\ it_{h-1} + b) \tag{2}$$

In Equation. (2), f is A nonlinear function, similar to A bias term is defined as a hyperbolic tangent and $b \in$ R. Using this convolution filter on every potential word window in the phrase, a feature map is created. Equation (3) is used to build this feature map:

$$C = \{(C_1, [C_2 - C_n - h + 1]) \tag{3}$$

Here $c \in Rn-h+1$. The maximum values corresponding to the filters are then generated on the feature map using a max-over-time pooling technique. In feature maps, this procedure aims to capture the most noticeable characteristics. The model uses a variety of filters and window sizes to identify various characteristics. The final, completely linked layer receives the outputs of the layer that contains these characteristics. A fully linked SoftMax layer is used to construct the probability distribution on the labels. In order to avoid overfitting, the CNN model employs 3 × 3 convolutional kernels activated with ReLU, max-pooling, batch normalization, and 0.4 dropouts. The training was done using the Adam optimizer with a 32 batch size, 30 epoch early stopping, and 0.001 the learning rate. The metric used is categorical cross entropy as loss function and F1-score, recall, accuracy, and precision as performance metric.

Performance Metrics

The classifier's performance is evaluated using a range of evaluation metrics. The assessment methods used in the study are explained below. A confusion matrix was used to represent classification accuracy objectively. The confusion matrix, which includes information on the actual and predicted classes that a classification system has generated, is one of the most popular ML techniques. The confusion matrix has two dimensions: Current and projected classes. A real-world class example is shown in each row, while the predicted class state is shown in each column. The values of the confusion matrix are as following:

- True positive (TP): The number of samples which it expected to be labeled positively and the number of samples which were actually labeled positively
- True negative (TN): The proportion of samples which were predicted to have negative labels and got negative results
- False positive (FP): This is the fraction of samples that were negatively labeled when they were not supposed to be
- False negative (FN): The proportion of samples that were tagged positively when they were predicted to be labeled negatively.

Accuracy: As a whole, the model's predictive power may be evaluated by comparing the percentage of all samples that were accurately predicted. The following equation of accuracy is Equation (4):

$$Accuracy = \frac{TP + TN}{TP + Fp + TN + FN} \tag{4}$$

Precision: This refers to the performance of the model, especially with regard to predicting the positive class; accuracy and recall were also used. In terms of precision, the rate at which anticipated positive samples actually yield positive results is quantified. What is meant by precision is Equation (5):

$$Precision \frac{TP}{TP + FP} \tag{5}$$

Recall: The term "recall" describes the percentage of truly positive samples that are tested. It is employed to calculate the proportion of properly detected real positives. The following equation of recall is Equation (6):

$$Recall \frac{TP}{TP + FN} \tag{6}$$

F1-score: The F1-score is a total score, using the F1-score helps reduce the bias that is incurred in optimizing only one metric by taking the harmonic mean of the two, which is defined as Equation (7):

$$F1 - Score = 2\frac{(Precision \times Recall)}{Precision + Reall} \tag{7}$$

Loss: The loss function quantifies how much the actual value deviates from the value predicted by the model.

RESULTS ANALYSIS AND DISCUSSION

The performance matrix is used in this section to understand the experiment outcomes of the suggested model. An Intel Core i7 CPU with the experimental setup had 16 GB of RAM, and eight cores running at 3.4 GHz. Python 3.9 was used in the Jupiter Notebook to execute all of the calculations, and the computer was running Windows 10. Table 2 displays a CNN model's performance on an apparel dataset. The precision of the model reaches the greatest value of 94.8%, whereas the accuracy is reported at 94.6%. The

Recall and F1-score are both reported at 94.7%. The results suggest that the CNN model exhibits high classification performance with minimal variation among the metrics.

The analysis of the CNN model's accuracy curve over eight epochs is shown in Figure 5. The x-axis depicts the total number of epochs and the y-axis represents the accuracy. The accuracy initially is about 65% and grows very rapidly reaching over 90% within the very first few epochs. The curve then stabilizes, demonstrating minimal fluctuation and converging at around 94%. The rapid convergence indicates effective learning and optimization during training.

In Figure 6, the loss curve represents the performance of a CNN model across six epochs.

Table 2: Results of CNN model on clothing dataset for online fashion retailing

Evaluation measures	Convolutional neural network
Accuracy	94.6
Precision	94.8
Recall	94.7
F1-score	94.7

CNN: Convolutional neural network

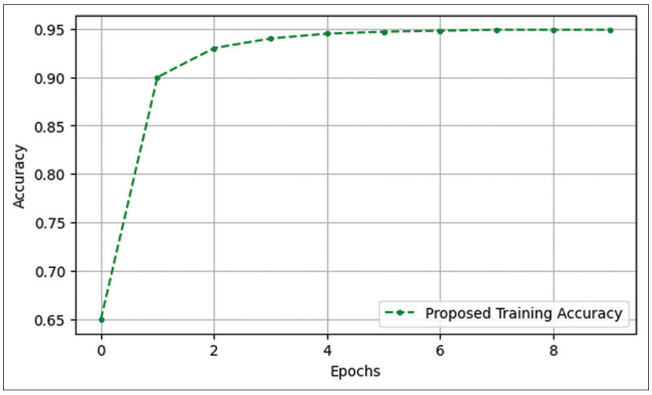

Figure 5: Plot for Accuracy curve of convolutional neural network

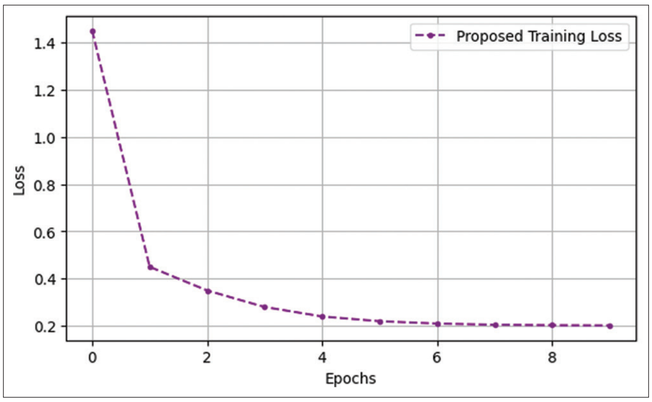

Figure 6: Plot of loss curve of convolutional neural network

On one side, it can see the total number of epochs, and on the other, it can see the values of the losses. The loss is very large at the start, about 1.5, but it quickly drops throughout the first few epochs, falling below 0.4. The curve continues to decline gradually and stabilizes around 0.2 after several epochs, indicating convergence. The steep decline in early training suggests effective learning, whereas the stabilization of loss values signifies proper optimization.

Figure 7 shows the confusion matrix and the performance of a classification model. The matrix comprises ten categories: Dress, Hat, Long Sleeve, Outwear, Pants, Shirt, Shoes, Shorts, Shirt, and T-shirt. The diagonal elements indicate the correctly classified instances, with Shoes achieving the highest correct predictions (72), followed by Long Sleeve (64) and Pants (42). Misclassification is observed in various categories, such as Long Sleeve being confused with T-shirts and Shirts being confused with similar clothing types. The overall classification performance suggests a strong model accuracy, yet with certain misclassification trends that need further optimization.

Comparative Analysis and Discussion

In this section, the output of the existing models on the same data set is compared with the proposed model. The following model comparisons are illustrated in Table 3.

The comparison and contrast of many DL models are compared on the basis of F1 score, recall,

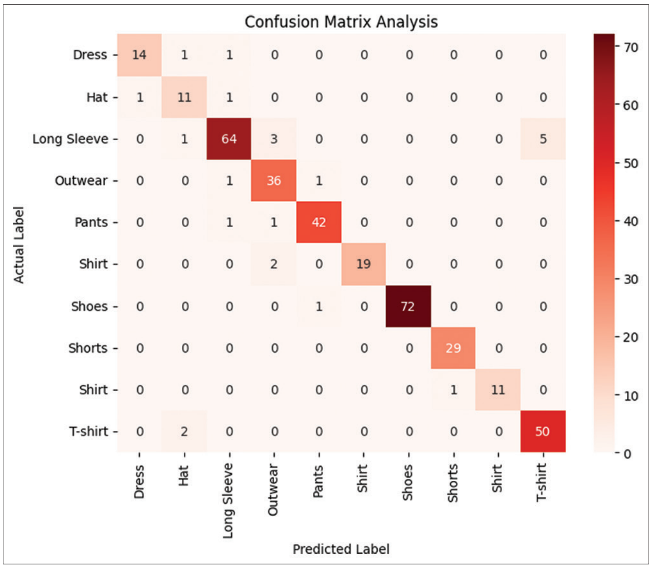

Figure 7: Confusion matrix of convolutional neural network model

Table 3: Comparison between models performance for online fashion retail on clothing dataset

Matrix	InceptionV3[21]	CNN
Accuracy	92.59	94.6
Precision	94.76	94.8
Recall	93.43	94.7
F1-score	94.08	94.7

CNN: Convolutional neural network

accuracy, and precision [Table 3]. When compared with other approaches, the CNN model achieves a 94.7% recall and F1 score, 94.6% accuracy, and a precision of 94.8%. The model with inceptionV3 performs better with an accuracy of 92.59%, precision of 94.76%, recall of 93.43%, and an F1-score of 94.08%. From the findings, it can see that It is clear that CNN is a better model than InceptionV3 for this particular job.

CONCLUSION AND FUTURE DIRECTION

There are significant potential prospects for companies in the clothes sales industry in the constantly growing online fashion market. Effective techniques for precisely recognizing clothing articles must be put in place in order to fully realize this potential. A DL model for garment categorization in online fashion retail is proposed in this study. According to the testing data, the CNN model beat benchmark models such as InceptionV3 and attained a high classification accuracy of 94.6%. The accuracy and loss curves indicated rapid convergence, whereas the confusion matrix revealed strong classification performance despite some misclassifications among visually similar apparel categories. Despite its effectiveness, the proposed CNN model has limitations, including a dataset that may not fully capture the diversity of clothing styles, textures, and lighting conditions. The model is purely image-based, lacking integration with textual data such as product descriptions or reviews, which could enhance classification accuracy. Future research could address these challenges by incorporating multi-modal learning, utilizing vision transformers, increasing the size of the dataset to improve generalization, and enhancing real-time inference for useful implementation.

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