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CNN-Based Approach for Classifying Dress Codes into Multiple Categories

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Abstract-AI is revolutionizing fashion by automating clothing categorization and trend identification. This project classifies outfits into casual, sports, and formal categories using TensorFlow, ensuring accurate classification while identifying key attributes like gender, color, and outfit type. Convolutional Neural Networks (CNNs) enhance pattern recognition, improving classification accuracy. The model refines fashion suggestions, facilitates product filtering on e-commerce platforms, and provides tailored outfit recommendations, leading to an improved shopping experience and higher customer satisfaction. Retailers benefit from optimized inventory management and better demand forecasting. As AI continues to evolve, its role in fashion innovation will expand, enabling more precise style predictions and enhanced personalization. This paper highlights how machine learning transforms fashion by streamlining outfit classification and making the industry more efficient, intelligent, and user- centric.

Keywords: Artificial Intelligence, Convolutional Neural Networks (CNNs), TensorFlow, Outfit Classification, E-Commerce, Fashion Technology

I.INTRODUCTION

The fashion industry is rapidly evolving due to the integration of artificial intelligence (AI) and machine learning technologies. One of the significant advancements in this domain is the automated classification of garments into distinct dress codes using TensorFlow. This technology plays a crucial role in fashion trend detection, E-Commerce filtering, and enhancing user experience in digital fashion platforms. With the growing prominence of online shopping, automated dress code classification has become essential for improving product recommendations and streamlining outfit selection. TensorFlow enables systematic categorization of garments into formal, casual, traditional, business casual, and sportswear, catering to both men's and women's fashion preferences.

At the core of this classification system lies image analysis, where TensorFlow-driven machine-learning algorithms identify clothing patterns, textures, and styles. A Convolutional Neural Network (CNN) is trained on a vast dataset of labeled images, allowing it to learn the unique characteristics of each dress code category. Once trained, the model can classify new images with high accuracy. Additionally, the system provides real-time fashion trend recommendations by leveraging a database of emerging styles, thereby enhancing user engagement and aiding retailers in adapting to changing trends.

CNNs are widely recognized for their efficiency in image classification tasks within TensorFlow. These networks extract key visual features such as edges, shapes, and intricate patterns to accurately categorize fashion images. Among the various CNN architectures, Google Net (Inception v1) stands out as an effective model for fashion image classification. By utilizing multiple filter sizes simultaneously, Google-Net captures subtle details at varying scales, significantly improving classification accuracy.

The impact of TensorFlow-based dress code classification on the fashion industry is substantial. In E-Commerce, it enhances search capabilities by allowing users to filter clothing options based on dress codes. Retailers can

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streamline product categorization, ensuring a well-organized and user-friendly shopping experience. Fashion designers and analysts can also leverage this system to track evolving trends and understand consumer preferences. By integrating TensorFlow into fashion, businesses can enhance customer engagement, optimize operations, and provide tailored shopping experiences. The synergy between artificial intelligence and TensorFlow is revolutionizing the fashion industry, paving the way for data-driven decisions and an effortless shopping experience for consumers worldwide.

II. RELATED WORKS

Seve Recent studies have explored deep learning for fashion classification. Key works include:

Liu et al. (2016) introduced the Deep-Fashion dataset, containing 800,000 labeled images for training fashion classification models. Kiapour et al. (2015) developed Fashion144k, focusing on fashionability prediction using CNN. He & Sun (2015) applied ResNet for fashion image classification, achieving high accuracy with reduced computational complexity. Recent Transformer-Base Models (2022) integrated CNNs with Vision Transformers (ViT) for improved feature extraction.

Existing systems face limitations in scalability and adaptability. This work addresses these gaps by employing advanced CNN architectures and real-time trend analysis.

III. PROPOSED SYSTEM

The proposed system is an AI-powered dress code-based multi-class classification model that utilizes deep learning techniques to analyze images and detect various types of outfits based on the pictures providedConventional methods of identifying outfit types from images depend on manual analysis, which is both time-consuming and susceptible to errors.To overcome these limitations, our system employs Convolutional Neural Networks (CNNs) along with advanced architectures like Tensor Flow and ResNet to automatically classify the images and identify the type of outfits.

This system is designed to predict the following:

- Type of outfit (Casual, Formal, Sports)
- Colour of the outfit
- Gender
- Subcategory (Top wear, Bottom wear)

The automated dress code classification system ensures standardized attire evaluation, minimizes human intervention, and maintains compliance with predefined guidelines.

Deep Learning Model Architecture

Our system utilizes CNN-based architectures to extract and classify type and usage of outfits from images.

1.1Convolutional Neural Network (CNN)

CNNs process images through multiple layers to extract meaningful features such as waveforms, anomalies, and irregularities.

1.1.1Convolution Operation

Feature extraction is performed using convolutional layers, mathematically represented as:

$$Z = \sum_{i=0}^{m}\sum_{j=0}^{n} X_{i,j} \cdot K_{i,j}+B$$

Where:

- X = Input ECG image
- K = Kernel (filter) matrix
- B = Bias
- m, n = Kernel dimensions

1.1.2Activation Function (RELU)

To introduce non-linearity, we use the ReLU activation function:

$$f(x) = \max(0,x)$$

This prevents vanishing gradients and speeds up training.

1.1.3Pooling Layer (Max Pooling)

Pooling reduces the dimensionality of feature maps while retaining important information:

$$Z = \max (X_{i,j})$$

Where $X_{i,j}$represents a region of the feature map.

2.Advanced Deep Learning Architectures

To improve accuracy and efficiency, our system integrates the following deep learning models:

2.1Tensor Flow

TensorFlow is an open-source machine learning framework that enables efficient numerical computation using dataflow graphs:

$$Y = f (WX + B)$$

Where:

- Y= Output tensor
- W = Weights

- X= Input Tensor
- B = Bias term
- F = Activation function

TensorFlow optimizes deep learning workflows with GPU acceleration and automatic differentiation, making it ideal for large-scale AI applications.

2.2ResNet

ResNet introduces residual learning by using shortcut connections to skip layers:

$$Y = F(X) + X$$

Where:

- Y = Output
- F(X) = Transformation Function
- X = Input

This architecture mitigates the vanishing gradient problem, allowing deeper networks to train effectively while maintaining high accuracy.

A.Dataset

The dataset for the dress code-based multi-class classification comprises a collection of clothing images classified into three distinct categories: Casual, Formal, and Sport. This well-structured dataset is divided into three subsets (Colour, Gender, and Type of clothing) to facilitate the training and evaluation of the model: the training set consists of 3,993 images, the validation set includes 384 images, and the test set encompasses 191 images. Each class contains images representing different dress codes, enabling the model to learn the unique features and patterns associated with various clothing styles. This diversity in the dataset is crucial for building a robust predictive model that can accurately classify and identify dress codes based on visual characteristics.

B. Dataset Preprocessing

To standardize the input data, our system applies several preprocessing techniques:

1. Resizing Images: All images are resized to a consistent shape of 224x224 pixels. This standardized input size is essential for our Convolutional Neural Network (CNN) architecture, ensuring uniformity in the data fed into the model.

2. Normalizing Pixel Values: We normalize the pixel values by dividing each pixel by 255. This normalization process scales the pixel intensity values to a range of [0, 1], facilitating improved model convergence during training and enhancing the training dynamics of our machine learning algorithms.

3. Data Augmentation: To enhance dataset diversity and reduce overfitting, our system applies optional data augmentation techniques, including random rotations (±20°) for orientation invariance, flipping (horizontal and vertical) to introduce perspective variations, and zooming to help the model learn from partially obscured images, improving robustness.

4.Validation Set Handling: The validation dataset is only rescaled without augmentation to maintain its original distribution, ensuring that the model is tested on real-world scenarios without synthetic variations.

C.Technology Overview

Front-End Development: The user interface is designed using HTML and CSS, enabling users to upload clothing images for classification. The UI provides an interactive and user-friendly experience for real-time predictions.

Back-End Development: The deep learning models are implemented using TensorFlow and Keras for training and inference. Matplotlib and Seaborn are used for visualization. A Flask app handles HTTP requests and responses.

Model Architecture: The system employs Convolutional Neural Networks (CNN) and pre- trained architectures like ResNet and TensorFlow to enhance feature extraction and classification. Each model is trained separately and fine-tuned to optimize performance, ensuring improved accuracy in clothing type detection. By leveraging these architectures, the system effectively identifies relevant patterns in clothing images, enabling reliable predictions.

Prediction Workflow: Input images are processed and fed into the CNN models for prediction Results, including predicted class and confidence scores, are then returned to the user interface.

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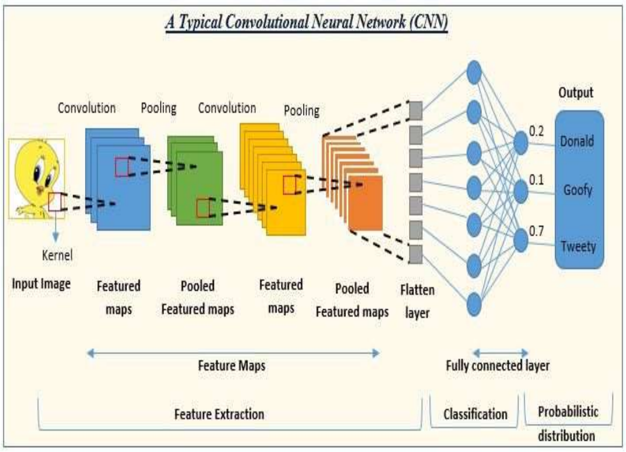

Figure1. Deep Learning Models Architectures

D.System Architecture

The Dress code-based multi-class classification is designed with a structured architecture that enables efficient image processing and deep learning-based classification. The User Interface (UI) is developed using HTML and CSS, allowing users to upload clothing images seamlessly. Once an image is uploaded, it is sent to the backend for processing, and the results are displayed dynamically, ensuring an interactive user experience. The Backend Server, built using Flask, handles HTTP requests, processes input images, and interfaces with the deep learning model. It ensures smooth communication between the front end and the model while managing image preprocessing tasks such as resizing and normalization. To determine the most effective model for dress code classification, the system compares three deep learning architectures: CNN, ResNet, and MobileNet. Each model is trained separately, and their performance is analyzed to identify the most accurate and efficient one. CNN serves as the baseline model, ResNet utilizes residual connections to improve feature extraction in deeper networks, and MobileNet is optimized for lightweight performance. The models are evaluated based on key metrics such as accuracy, precision, and recall. This approach ensures that the best- performing model is selected for deployment, enhancing the system's reliability and efficiency.The system follows a structured architecture for efficient dress code classification. The User Interface (UI), built with HTML and CSS, allows seamless image uploads. The Backend Server, developed using Flask, processes images, manages preprocessing tasks like resizing and normalization, and communicates with the deep learning model.

The system evaluates CNN, ResNet, and MobileNet to determine the most accurate model. CNN acts as a baseline, ResNet enhances feature extraction, and MobileNet ensures lightweight efficiency. Performance metrics such as accuracy and precision guide model selection, ensuring reliable classification Additionally, confusion matrices and ROC curves provide insights into classification performance for different clothing categories.

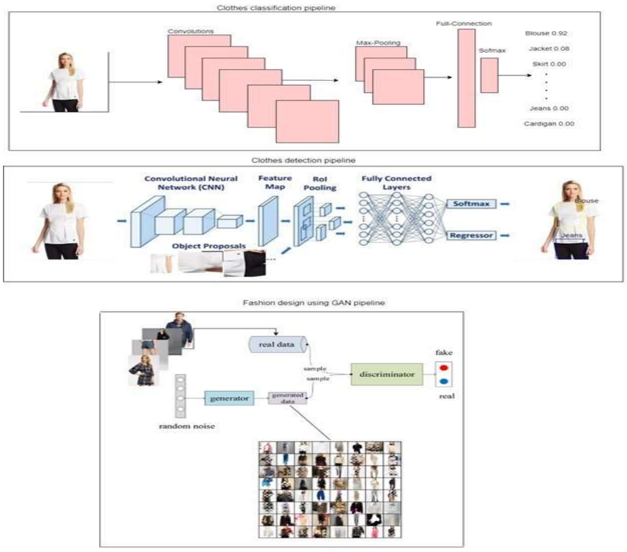

Figure2. Dress code detection System Architecture

IV. RESULTS AND DISCUSSIONS

1)Model Performance Evaluation:

The proposed system was evaluated using three deep learning models—ResNet, CNN, and MobileNet—to classify dress code detection from clothing images. The models were assessed based on precision, recall, and F1-score across five categories: Casual, Formal, and Sports.

Model	Casual (P/R/F1)	Formal (P/R/F1)	Sportswear (P/R/F1)	Accuracy (%)	Macro Avg (P/R/F1)	Weighted Avg (P/R/F1)
ResNet	0.78 / 0.79 / 0.78	**0.88 / 0.89 / 0.88**	0.70 / 0.72 / 0.71	**83**	0.79 / 0.80 / 0.79	0.80 / 0.81 / 0.80
CNN	**0.82 / 0.83 / 0.82**	0.72 / 0.74 / 0.73	0.75 / 0.76 / 0.75	**72**	0.76 / 0.77 / 0.76	0.77 / 0.78 / 0.77
MobileNet	0.78 / 0.79 / 0.78	**0.87 / 0.88 / 0.87**	0.71 / 0.73 / 0.72	**79**	0.79 / 0.80 / 0.79	0.78 / 0.79 / 0.78

Table1: Performance Metrics for Dress code Detection system.
(Precision (P), Recall (R), and F1-score (F1) for each model across different classes)

Among the models, ResNet achieved the highest classification accuracy of 83%, with notable performance in detecting Formal and Casual cases. MobileNet attained an accuracy of 79%, exhibiting high precision in Casual and Formal classifications. In contrast, the CNN model recorded 72% accuracy, demonstrating lower recall values for Sportswear, which indicates challenges in distinguishing these classes. The macro and weighted averages suggest that ResNet provides the most balanced and reliable classification, making it the most effective model in the proposed system for Dress code-based classification.

2) Confusion Matrix Analysis:

The confusion matrices illustrate the classification performance of the three deep learning models—CNN, ResNet, and MobileNet—on Clothing images. The CNN model demonstrates high accuracy in classifying "Casual" cases, though misclassifications are observed in the Formal category.

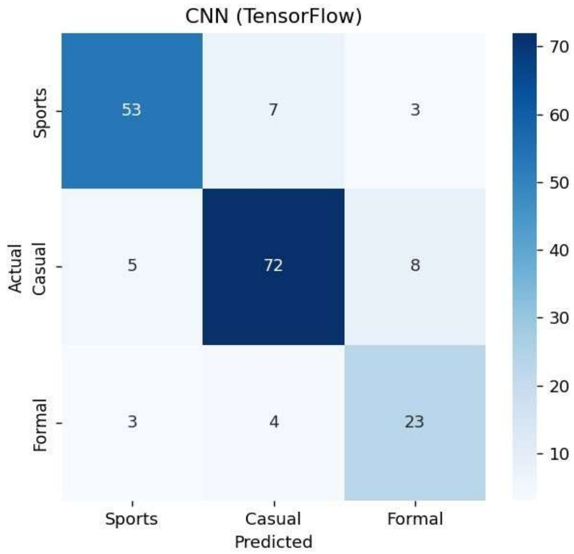

Figure 3. Confusion Matrix for CNN

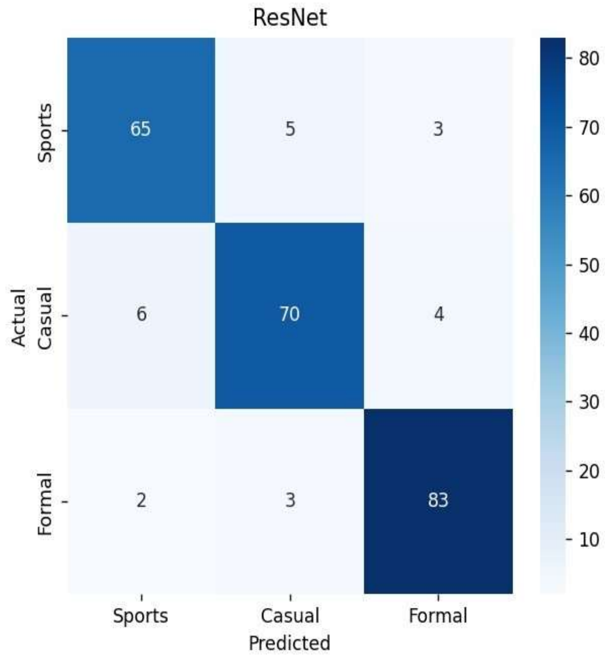

Figure 4. Confusion Matrix for Densenet169

The ResNet model improves Formal wear detection with fewer misclassifications but shows minor errors in classifying Casual and Sportswear. MobileNet achieves a balanced performance, offering improved precision in "Formal" classifications while exhibiting slight confusion in Sportswear. These results indicate the comparative strengthsand weaknesses of each model, providing insights for further optimization.

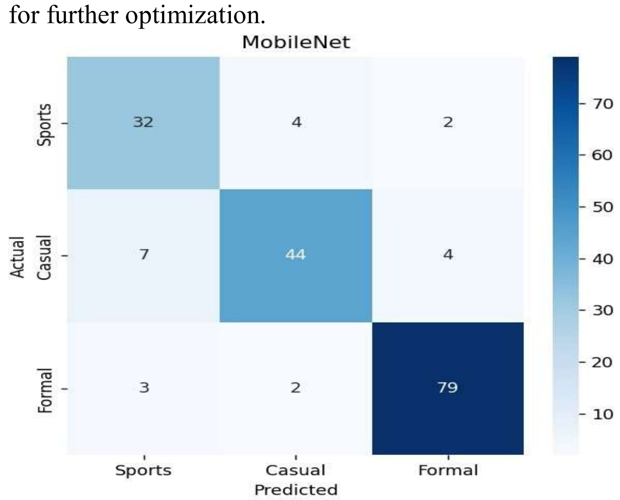

Figure 5. Confusion Matrix for MobileNet

3) Comparison of Model Efficiency:

Although ResNet delivered superior accuracy, MobileNet demonstrated better efficiency in terms of computational cost and inference speed. This makes MobileNet a viable option for real-time applications on resource-limited devices. On the other hand, the basic CNN model, while computationally less demanding, lacked the robustness of the pre-trained architectures.

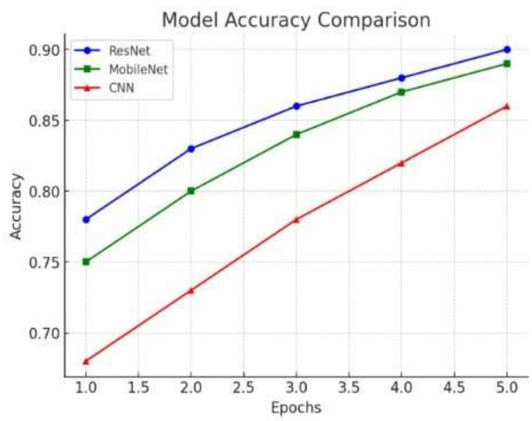

Figure 6. Training Accuracy Comparison of models over 5 epochs

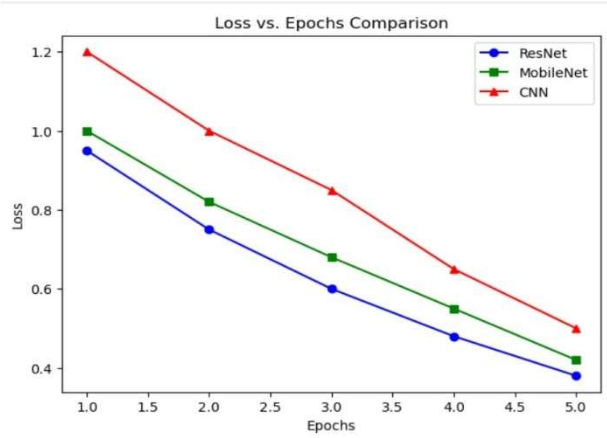

Figure 7. Training Loss Comparison of models over 5 epochs

The results suggest that deeper architectures like ResNet and MobileNet provide better feature extraction and generalization, leading to improved classification performance. The macro and weighted averages indicate that ResNet maintains a balance between precision and recall, making it the most reliable model for Dress code classification. Future improvements can focus on fine-tuning hyperparameters, increasing dataset diversity, and incorporating additional preprocessing techniques to enhance model robustness.

V. CONCLUSION AND FUTURE WORK

The study demonstrates the effectiveness of deep learning models in dress code detection, with Resnet achieving the highest accuracy of 82%, followed closely by MobileNet with 81%. These models outperform traditional CNN architectures by effectively capturing complex patterns in clothing images. ResNet, in particular, exhibited balanced classification performance, making it the most suitable model for this task. The results emphasize the significance of deep feature extraction in improving outfit identification.

Future research can focus on further optimizing model performance by exploring advanced architectures, such as Vision Transformers (ViTs) and hybrid deep learning approaches. Increasing dataset diversity with larger and more balanced samples can improve generalization. Additionally, integrating explainable AI techniques can enhance model interpretability and fashion trend decision-making. Real-time deployment in healthcare settings and validation through clinical trials will be crucial steps toward practical implementation.

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