A Minor Project Report on

FASHION MNIST

Submitted in Partial fulfillment of requirements for the award of the degree of

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

By

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Under the guidance of

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

KESHAV MEMORIAL INSTITUTE OF TECHNOLOGY

(AN AUTONOMOUS INSTITUTION)

Accredited by NBA & NAAC, Approved by AICTE, Affiliated to JNTUH.

Narayanaguda, Hyderabad, Telangana-29

2023-24

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CERTIFICATE

This is to certify that this is a bonafide record of the report titled **"FASHION MNIST"** which is being presented as the minor project by

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In partial fulfillment for the award of the degree of Bachelor of Technology in Computer Science and Engineering affiliated to the Jawaharlal Nehru Technological University Hyderabad, Hyderabad

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PEO4: Graduates will communicate effectively, work collaboratively and exhibit high levels of professionalism and ethical responsibility.

DECLARATION

We hereby declare that the results embodied in the dissertation entitled **"FASHION MNIST"** has been carried out by us together during the academic year 2023-24 as a partial fulfillment of the award of the B.Tech degree in Computer Science and Engineering from JNTUH. We have not submitted thisreport to any other university or organization for the award of any other degree.

Student Name	**Rollno.**
MOLLY SHARMA	**20BD1A0555**

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ABSTRACT

The Fashion MNIST(Modified National Institute of Standards and Technology) dataset is a large database of fashion images that is used for training and testing various machine learning systems. The main reason for fashion item classification lies in the need to efficiently organize, search, and understand the vast and diverse world of fashion. Fashion items encompass a wide range of products, including clothing, accessories, footwear, and more; each with numerous variations in style, design, and characteristics. Classification allows for the systematic categorization of these items, enabling businesses and consumers to navigate and make sense of the vast fashion landscape. Overall, fashion item classification is driven by the need for efficient organization, effective inventory management, personalized recommendations, and enhanced consumer experiences. By categorizing and understanding fashion items, businesses and customers can navigate the ever-evolving fashion world with ease and make informed decisions.

The classification of fashion items covers a wide range .Classification plays a crucial role in improving a variety of aspects of the fashion ecosystem, including personal styling, e-commerce, and retail, as well as fashion trend analysis. Accurate classification makes it possible for customers to have a seamless shopping experience in e-commerce thanks to personalized recommendations and efficient product searches. It makes it easier for retailers to plan their assortments, optimize their supply chains and manage their inventory. Visual search and similarity matching are also made possible by classification, allowing users to find fashion items based on their preferences and visually similar products. Along with SVM(Support Vector Machine) classification, the primary goal of using CNN(Convolutional Neural Network) for fashion product classification is to achieve high accuracy in classifying fashion products and to ensure that the model is resistant to changes in background and lighting in the input images.it should accommodate many product categories and images, the model ought to be scalable.

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Introduction

1.1 Motivation

The main reason for fashion item classification lies in the need to efficiently organize, search, and understand the vast and diverse world of fashion. Fashion items encompass a wide range of products, including clothing, accessories, footwear, and more, each with numerous variations in style, design, and characteristics. Classification allows for the systematic categorization of these items, enabling businesses and consumers to navigate and make sense of the vast fashion landscape. Overall, fashion item classification is driven by the need for efficient organization, effective inventory management, personalized recommendations, and enhanced consumer experiences. By categorizing and understanding fashion items, businesses, and customers can navigate the ever- evolving fashion world with ease and make informed decisions.

1. **Learning Image Classification:** Fashion MNIST is a dataset of grayscale images of 10 different clothing items. Working on this project provides an excellent opportunity to delve into image classification, a fundamental task in computer vision.

2. **Understanding Deep Learning Concepts:** Implementing a neural network or a convolutional neural network (CNN) for Fashion MNIST allows you to grasp key concepts in deep learning, such as model architecture, training, and evaluation.

3. **Practical Application of Machine Learning:** Fashion MNIST is a real-world dataset that has practical applications in the fashion industry. By working on this project, you gain experience in applying machine learning to solve real-world problems.

4. **Portfolio Development:** If you are building a portfolio for a job in data science, machine learning, or related fields, a Fashion MNIST project can serve as a tangible example of your skills and abilities to prospective employers.

5. **Experimentation with Hyperparameters:** You can use the Fashion MNIST project as a playground to experiment with hyperparameters, model architectures, and optimization techniques to enhance your understanding of the impact of these factors on model performance.

6. **Transfer Learning Opportunities:** After successfully building a model for Fashion MNIST, you can

explore transfer learning by applying your model to other image classification tasks or datasets. This extends the value of your project and broadens your understanding of model generalization.

7. **Community Engagement:** Fashion MNIST is a well-known dataset in the machine learning community. Engaging in discussions, sharing your code, and seeking feedback can help you connect with other enthusiasts and professionals in the field.

8. **Visualization Skills:** Working with image data allows you to develop skills in visualizing data and understanding the patterns learned by your model. You can create visualizations that showcase the activation maps, feature representations, and other aspects of your model's inner workings.

9. **Benchmarking and Comparison:** Fashion MNIST is often used as a benchmark dataset for testing and comparing different machine learning models. By participating in this, you can evaluate your model against existing solutions and explore opportunities for improvement.

10. **Problem-Solving Skills:** Tackling a real-world dataset like Fashion MNIST helps you hone your problem-solving skills. You'll encounter challenges related to data preprocessing, model selection, and performance optimization, providing valuable learning experiences.

In summary, the motivation for a Fashion MNIST project can range from skill development and portfolio building to a genuine interest in fashion-related applications of machine learning. The project offers a diverse set of challenges that can contribute significantly to your growth as a machine learning practitioner.

1.2 Scope

The classification of fashion items covers a wide range of applications in the fashion industry. Classification plays a crucial role in improving a variety of aspects of the fashion ecosystem, including personal styling, e-commerce, and retail, as well as fashion trend analysis. Accurate classification makes it possible for customers to have a seamless shopping experience in e-commerce thanks to personalized recommendations and efficient product searches. It makes it easier for retailers to plan their assortments, optimize their supply chains, and manage their inventory. Visual search and similarity matching are also

made possible by classification, allowing users to find fashion items based on their preferences and visually

similar products.

1.3 Objectives

Along with SVM classification, the primary goal of using CNN for fashion product classification is to achieve high accuracy in classifying fashion products and to ensure that the model is resistant to changes in background and lighting in the input images. it should accommodate a large number of product categories and images, the model ought to be scalable. Users should be able to understand how the model makes its classification decisions if it has some degree of interpretability.

1. **Build a Baseline Model:**
    - Objective: Develop a basic neural network or convolutional neural network (CNN) as a baseline model for Fashion MNIST.
    - Key Results: Achieve a reasonable accuracy on the test set to establish a baseline performance level.
2. **Experiment with Model Architectures:**
    - Objective: Explore different neural network architectures to improve model performance.
    - Key Results: Compare the accuracy, training time, and model complexity of different architectures.
3. **Optimize Hyperparameters:**
    - Objective: Fine-tune hyperparameters to improve the model's learning and generalization capabilities.
    - Key Results: Identify optimal values for learning rate, batch size, and other hyperparameters.
4. **Data Preprocessing and Augmentation:**
    - Objective: Implement data preprocessing techniques and augmentation to enhance the model's robustness.
    - Key Results: Improve model performance by addressing issues like overfitting and data variability.
5. **Evaluate Model Performance:**
    - Objective: Assess the model's performance using relevant metrics such as accuracy, precision,
    - recall, and F1 score.

- Key Results: Provide a comprehensive evaluation of the model's strengths and weaknesses.

1.4 Outcomes

Accurate classification of fashion products can improve the customer experi- ence by enabling better search and filtering options. the accurate classification of fashion products can also help retailers manage their inventory more ef- fectively. CNN is a powerful deep-learning technique that can improve the accuracy of fashion product classification. and using CNN along with SVM.

1. **Interpretability Visualizations:**
    - Outcome: Generate visualizations (e.g., activation maps, heatmaps) to interpret and understand the model's decision-making process.
    - Significance: Increases transparency and trust in your model by making its predictions more interpretable.
2. **Successful Transfer Learning (if applicable):**
    - Outcome: Apply transfer learning successfully, demonstrating the adaptability of your model to other image classification tasks.
    - Significance: Highlights the versatility of your model beyond the original dataset.
3. **Optimized Training Process:**
    - Outcome: Optimize the training process for efficiency, potentially reducing training time and resource requirements.
    - Significance: Enhances the scalability and practicality of deploying your model in real-world scenarios.
4. **Community Engagement and Feedback:**
    - Outcome: Engage with the machine learning community, share your project, and receive valuable feedback.
    - Significance: Fosters collaboration, networking, and continuous learning within the community.
5. **Documented Project:**

- Outcome: Create comprehensive documentation covering project overview, methodology, results, and future recommendations.
- Significance: Facilitates knowledge sharing and replication of your work by others.

Literature Survey

2.1 Literature Review

[1]. ”Fashion-MNIST: A Novel Image Dataset for Benchmarking Machine Learning Algorithms” by Han Xiao et al. (2017) This paper introduces the Fashion MNIST dataset, which consists of 60,000 fashion item images for classification tasks. It discusses the use of CNNs for fashion item classification and highlights the importance of benchmark datasets in evaluating classification algorithms.

[2]. ”Fashion Apparel Classification using Deep Learning” by Yash Mehta et al. (2018) The authors propose a CNN-based approach for fashion item classification, leveraging transfer learning and fine-tuning techniques. They experiment with different CNN architectures and evaluate the classification performance on a custom fashion dataset. SVM is incorporated for decision boundary construction and classification.

[3]. ”Deep Convolutional Neural Networks for Fashion Image Classification and Retrieval” by Zuxuan Wu et al. (2018) This research focuses on fashion image classification and retrieval using deep CNNs. It explores various CNN architectures and investigates the combination of CNN with SVM for fashion item classification. The study compares the performance of different models on public fashion datasets.

[4]. ”Multi-Scale Convolutional Neural Networks for Fashion Image Classi- fication” by Junyu Dong et al. (2018) The authors propose a multi-scale CNN approach for fashion image classification, addressing the challenge of scale variations in fashion items. They integrate SVM for the final classification decision and evaluate the performance on large-scale fashion datasets.

2.2 Literature Summary

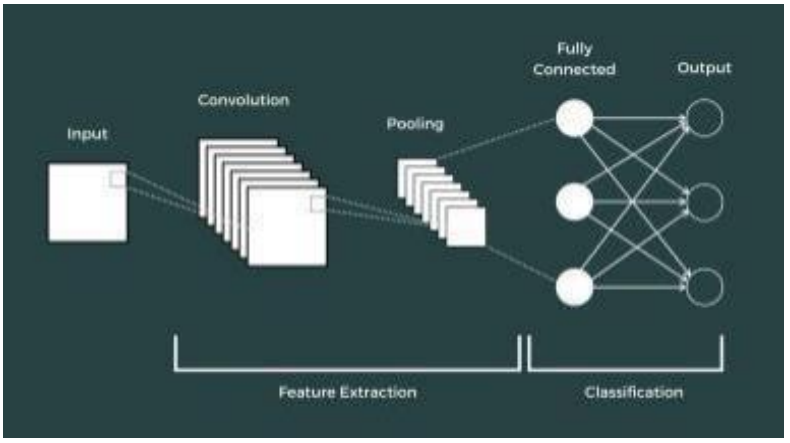
2.2.1 CNN for fashion items classification • CNNs have demonstrated remarkable success in various computer vision tasks, including fashion item classification • Pre-trained CNN models trained on large-scale datasets (e.g., ImageNet and fashion MNIST) are commonly used, followed by fine-tuning or transfer learning for fashion-specific classification tasks. • CNNs capture hierarchical visual features, enabling the recognition of complex patterns, textures, and styles inherent in fashion items.

2.2.2 SVM for fashion items classification • SVMs are popular algorithms for classification tasks due to their ability to construct optimal decision boundaries. • SVMs achieve good generalization and robustness by maximizing the margin between different fashion item classes. • SVMs provide interpretable results by identifying support vectors, which help understand the critical features contributing to the classification decision.

Methodology

3.1 Proposed Method and Algorithms

3.1.1 Convolution Neural Networks (CNN) Convolution neural networks are powerful deep learning architectures designed for image classification tasks. They consist of multiple convolutions and pooling layers that extract relevant features from input images. Convolu- tion neural networks are highly effective in capturing spatial relationships and patterns



For a Fashion MNIST project, you can use various methods and algorithms to achieve image classification. Here's a proposed approach that involves a Convolutional Neural Network (CNN), a commonly used architecture for image classification tasks:

Proposed Method:

1. **Data Exploration:**

    - Explore the Fashion MNIST dataset to understand its structure, the distribution of classes, and the characteristics of the images.

2. **Data Preprocessing:**

- Normalize pixel values to a range between 0 and 1 to aid convergence during training.
- Explore and implement data augmentation techniques to increase the diversity of the training set (e.g., random rotations, flips, and shifts).

3. **Model Architecture:**

   - Build a Convolutional Neural Network (CNN) for image classification. Here's a simple example:

     model = Sequential()

     model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))

     model.add(MaxPooling2D((2, 2)))

     model.add(Conv2D(64, (3, 3), activation='relu'))

     model.add(MaxPooling2D((2, 2)))

     model.add(Conv2D(64, (3, 3), activation='relu'))

     model.add(Flatten())

     model.add(Dense(64, activation='relu'))

     model.add(Dense(10, activation='softmax'))

4. **Compile the Model:**

   - Choose an appropriate optimizer (e.g., Adam), a loss function (e.g., categorical crossentropy for multiclass classification), and evaluation metric (e.g., accuracy).

     model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

5. **Model Training:**

   - Train the model on the training data using the compiled architecture.

     model.fit(train_images, train_labels, epochs=10, batch_size=64, validation_data=(val_images, val_labels))

6. **Model Evaluation:**

   - Evaluate the model on the test set to assess its generalization performance.

     test_loss, test_acc = model.evaluate(test_images, test_labels) print(f'Test Accuracy: {test_acc}')

7. **Hyperparameter Tuning:**
    - Experiment with hyperparameter tuning to optimize the model's performance (e.g., learning rate, batch size).
8. **Visualization:**
    - Visualize the model's performance using confusion matrices, ROC curves, and other relevant visualizations.
9. **Transfer Learning (Optional):**
    - Consider exploring transfer learning using pre-trained models (e.g., VGG16, ResNet) to improve performance, especially if you have limited data.
10. **Documentation:**
    - Document the entire process, including data preprocessing steps, model architecture, training configuration, and results.
11. **Deployment (Optional):**
    - If applicable, explore options for deploying the trained model for inference in real-world applications.

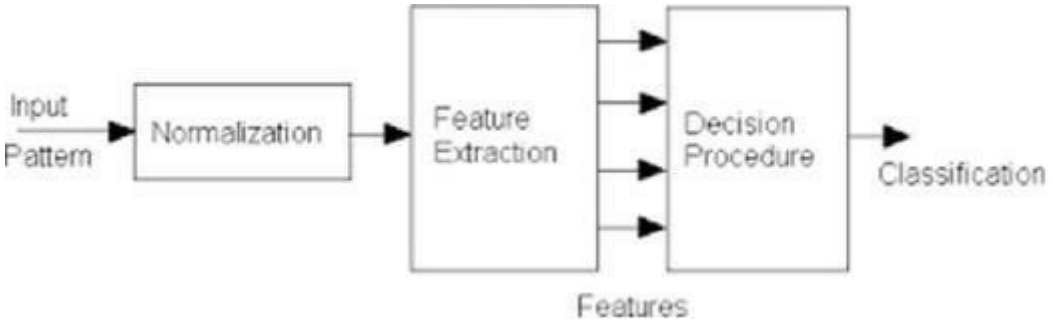
Note:

- Adjust the complexity of the model based on the computational resources available and the scale of the project.
- Experiment with different architectures, hyperparameters, and regularization techniques to find the best combination for your specific task.
- Use tools like TensorBoard for visualizing training metrics and model performance during training.

This proposed method provides a solid foundation for building and training a CNN for the Fashion MNIST classification task. Feel free to adapt and expand upon this approach based on your specific objectives and constraints.

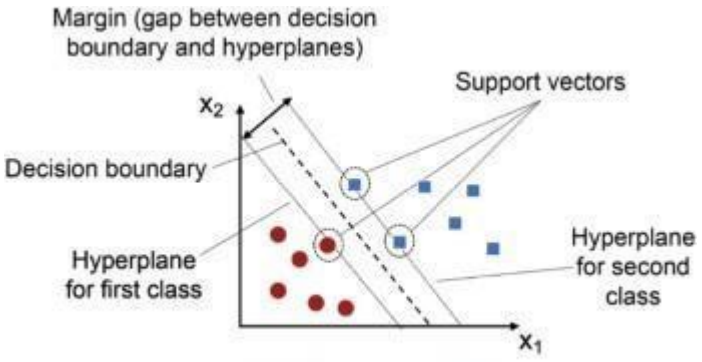
3.1.2 Feature Extraction

Feature extraction is a process in machine learning and computer vision that involves transforming raw input data, such as images or text, into a more compact and representative feature representation. It aims to capture the most relevant and discriminative information from the data, enabling effective pattern recognition and analysis.



3.1.3 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a popular supervised machine learning algorithm used for classification and regression tasks. It aims to find an optimal hyperplane that separates different classes in the input data by maximizing the margin between them. SVM can handle both linearly separable and non linearly separable data by using kernel functions to transform the input space



Proposed SVM Approach for Fashion MNIST:

1. **Data Preprocessing:**
    - Flatten the 28x28 images into 1D arrays, making each image a feature vector.
    - Normalize pixel values to a range between 0 and 1.
2. **Data Splitting:**
    - Split the dataset into training and testing sets.

      from sklearn.model_selection import train_test_split X_train, X_test, y_train, y_test = train_test_split(data, labels, test_size=0.2, random_state=42)
3. **Model Training:**
    - Train a Support Vector Machine classifier on the training data.
4. **Model Evaluation:**
    - Evaluate the SVM classifier on the test set.

pythonCopy code from sklearn import svm

Flatten images for SVM

X_train_flat = X_train.reshape(X_train.shape[0], -1)

X_test_flat = X_test.reshape(X_test.shape[0], -1)

Create an SVM classifier

clf = svm.SVC(kernel='linear', C=1)

Train the classifier

clf.fit(X_train_flat, y_train) from sklearn.metrics import accuracy_score, classification_report # Make predictions on the test set y_pred = clf.predict(X_test_flat) # Calculate accuracy accuracy = accuracy_score(y_test, y_pred) print(f'Accuracy: {accuracy}') # Display classification report print(classification_report(y_test, y_pred))

Hyperparameter Tuning:

- Experiment with different hyperparameters, such as the choice of kernel ('linear', 'rbf', etc.) and the regularization parameter (C), to optimize the SVM's performance.

  RBF kernel with different C values clf_rbf = svm.SVC(kernel='rbf', C=1)

5. **Visualization (Optional):**

   - Visualize the decision boundaries and support vectors to gain insights into how the SVM is making predictions.

6. **Documentation:**

   - Document the SVM model, hyperparameters, and evaluation results for future reference.

Note:

- SVMs with a linear kernel are a good starting point, but you can experiment with other kernels like radial basis function (RBF) depending on the characteristics of your data.
- SVMs may require more computational resources, especially for large datasets. Consider using a subset of the Fashion MNIST dataset for initial experimentation.
- Feature scaling is essential for SVMs, so normalizing pixel values is crucial.
- The choice of hyperparameters, especially the regularization parameter (C), can significantly impact the SVM's performance.

This proposed SVM approach provides a basic framework for using SVMs on the Fashion MNIST dataset. Adjust and refine the approach based on your specific objectives and requirements.

Implementation

Training a Support Vector Machine (SVM) classifier involves fitting the model to a labeled dataset, where each data point is associated with a specific class label. Here is a general outline of the steps involved in training an SVM classifier:

1. **Import Libraries:**

- Import the necessary libraries, typically including scikit-learn for SVM implementation.

```python
from sklearn import svm
```

2. **Load and Preprocess Data:**

- Load your dataset and preprocess it as needed. Ensure that you have features (X) and corresponding labels (y).

```python
# Example: Assuming you have a dataset X_train, y_train for training
```

3. **Create SVM Model:**

- Choose the appropriate SVM model for your task (e.g., linear SVM, kernel SVM), and create an instance of the SVM classifier.

```python
```

```
# Example: Linear SVM
clf = svm.SVC(kernel='linear')
```

4. **Train the SVM Model:**

- Train the SVM model on the training data.

```python
clf.fit(X_train, y_train)
```

5. **Model Evaluation (Optional):**

- If you have a separate test set, evaluate the model's performance on the test set.

```python
# Example: Assuming you have a test set X_test, y_test
accuracy = clf.score(X_test, y_test)
print(f'Test Accuracy: {accuracy}')
```

6. **Hyperparameter Tuning (Optional):**

- Experiment with different hyperparameter values to optimize the model's performance. Grid search or randomized search can be used for hyperparameter tuning.

```python
from sklearn.model_selection import GridSearchCV

# Example: Perform grid search for hyperparameter tuning
param_grid = {'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf']}
grid_search = GridSearchCV(clf, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Get the best hyperparameters
best_params = grid_search.best_params_
```

7. **Save the Trained Model (Optional):**

- Save the trained SVM model for future use.

```python
import joblib

# Save the model
joblib.dump(clf, 'svm_model.pkl')
```

Note:

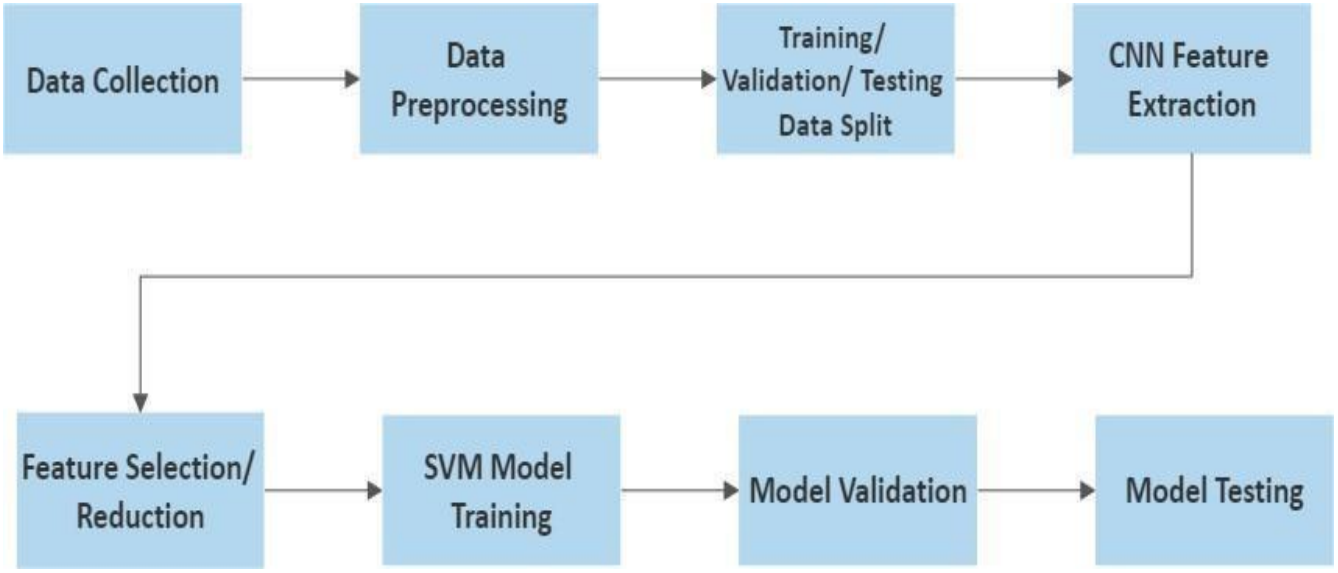
- The choice of the SVM kernel (e.g., 'linear', 'rbf') depends on the characteristics of your data. Linear kernels work well for linearly separable data, while radial basis function (RBF) kernels can capture more complex relationships.

- The regularization parameter (`C` in scikit-learn) influences the trade-off between achieving a smooth decision boundary and classifying training points correctly. Experiment with different values to find the optimal balance.

- Depending on the size of your dataset, training an SVM can be computationally expensive. Consider using a subset of your data for initial experimentation.

Adjust the code snippets based on the specifics of your dataset and the task you're working on. Training an SVM involves finding the optimal hyperplane that best separates the data into different classes while maximizing the margin between classes. The process might require some experimentation and fine-tuning to achieve the best results.

4.1 Process Model Figure



4.1: Process Flow

4.1.1 Dataset

The Fashion-MNIST dataset is a benchmark dataset commonly used in the field of computer vision and machine learning for fashion item classification tasks. It serves as an alternative to the well-known MNIST handwritten digits dataset and provides a more challenging and realistic problem domain. The Fashion-MNIST dataset consists of a large collection of 60,000 grayscale images of fashion items belonging to ten different classes, with 6,000 images per class. Additionally, there is a separate test set containing 10,000 images.

4.1.2 Feature Extraction

CNN feature extraction in fashion items classification involves passing images through pre-trained CNN models to capture patterns, textures, and shapes. The last convolutional layer's output is used to obtain a fixed- 7 length feature vector representing the image, facilitating accurate and robust classification.

4.1.3 Feature Representation

Feature representation is a critical step in fashion items classification. In the context of fashion items, feature representation involves converting the extracted visual features, such as patterns, textures, and shapes, into fixed-length feature vectors. These feature vectors capture the essential information of the fashion items and serve as input for classification algorithms like Support Vector Machines (SVM), facilitating accurate and efficient classification of fashion items into different categories.

4.1.4 Training SVM Classifier

In the process of training a classifier with svm using the extracted feature vectors from fashion item images, the SVM learns to separate different classes by finding an optimal hyperplane in the feature space. During training, the SVM adjusts its parameters, such as the C regularization parameter and kernel type, to maximize the margin between classes and minimize classification errors. This process enables the SVM to accurately classify fashion items based on their extracted features, facilitating effective fashion items classification.

4.1.5 Model Evaluation and Optimization

In model evaluation, the trained model is tested on a separate dataset, and metrics such as accuracy, precision, recall, and F1-score are computed. Based on the evaluation results, the model can be further optimized by adjusting hyperparameters, refining the feature representation, or exploring ensemble methods. Continuous evaluation and optimization help improve the model's accuracy and generalization ability for reliable fashion items classification.

Hyperparameter Tuning:

- Experiment with different hyperparameter values to find the combination that optimizes your model's performance.
- Use techniques like grid search or randomized search to efficiently explore the hyperparameter space.

Results and Analysis

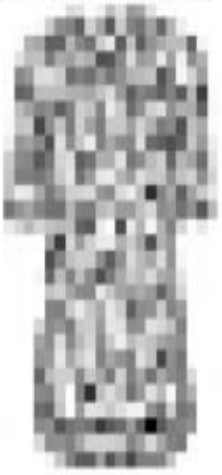
5.1 Findings and Result

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_1 (Conv2D)           (None, 25, 25, 32)        544

 max_pooling2d_1 (MaxPooling  (None, 12, 12, 32)       0
 2D)

 flatten (Flatten)           (None, 4608)              0

 dense (Dense)               (None, 128)               589952

 dense_1 (Dense)             (None, 10)                1290

=================================================================
Total params: 591,786
Trainable params: 591,786
Non-trainable params: 0
_________________________________________________________________
```

Actual = Bag / 8
Predicted = Bag / 8

Actual = Sneakers / 7
Predicted = Sneakers / 7

Actual = Shirt / 6
Predicted = Shirt / 6



Actual = Bag / 8
Predicted = Bag / 8

Actual = Sneakers / 7
Predicted = Sneakers / 7

Actual = Dress / 3
Predicted = Dress / 3

Actual = Coat / 4
Predicted = Coat / 4

Actual = Dress / 3
Predicted = Dress / 3

	precision	recall	f1-score	support
T-shirt/top	0.85	0.86	0.86	1000
Trouser	0.99	0.98	0.98	1000
Pullover	0.87	0.85	0.86	1000
Dress	0.90	0.92	0.91	1000
Coat	0.79	0.91	0.85	1000
Sandle	0.97	0.98	0.98	1000
Shirt	0.80	0.66	0.72	1000
Sneakers	0.92	0.98	0.95	1000
Bag	0.98	0.97	0.98	1000
Ankle boot	0.99	0.92	0.95	1000
accuracy			0.90	10000
macro avg	0.91	0.90	0.90	10000
weighted avg	0.91	0.90	0.90	10000

5.2 Overall Results

Model	Accuracy
CNN	83.28
CNN+SVM	90.95

Code

1. Import the libraries

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
import keras
```

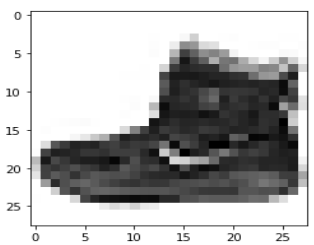
2. Loading the data

```
(X_train, y_train), (X_test, y_test)=tf.keras.datasets.fashion_mnist.load_data()
```

Output:

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-labels-idx1-ubyte.gz
32768/29515 [================================] - 0s 0us/step
40960/29515 [========================================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-images-idx3-ubyte.gz
26427392/26421880 [==============================] - 0s 0us/step
26435584/26421880 [==============================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-labels-idx1-ubyte.gz
16384/5148 [===============================================================================================] - 0s 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-images-idx3-ubyte.gz
4423680/4422102 [==============================] - 0s 0us/step
4431872/4422102 [==============================] - 0s 0us/step
```

3. Initial Image



4. Blur image with labels


Coat / 4
Shirt / 6
T-shirt/top / 0
Sandal / 5
Shirt / 6
Dress / 3
Shirt / 6
Sandal / 5
Coat / 4
Coat / 4
Dress / 3
T-shirt/top / 0
Trouser / 1
Ankle boot / 9
Dress / 3
Pullover / 2
Pullover / 2
Sneaker / 7
Sneaker / 7
Sneaker / 7
Shirt / 6
Sneaker / 7
Coat / 4
Coat / 4
Coat / 4

Building the CNN Model

```
model=keras.models.Sequential([

    keras.layers.Conv2D(filters=32,kernel_size=3,strides=(1,1),padding='valid',activ
    ation='relu',input_shape=[28,28,1]),
                            keras.layers.MaxPooling2D(pool_size=(2,2)),
                        keras.layers.Flatten(),
                            keras.layers.Dense(units=128,activation='relu'),
                            keras.layers.Dense(units=10,activation='softmax'))]
```

Output

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 26, 26, 32)        320
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 13, 13, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 5408)              0
_________________________________________________________________
dense (Dense)                (None, 128)               692352
_________________________________________________________________
dense_1 (Dense)              (None, 10)                1290
=================================================================
Total params: 693,962
Trainable params: 693,962
Non-trainable params: 0
```

Images with labels

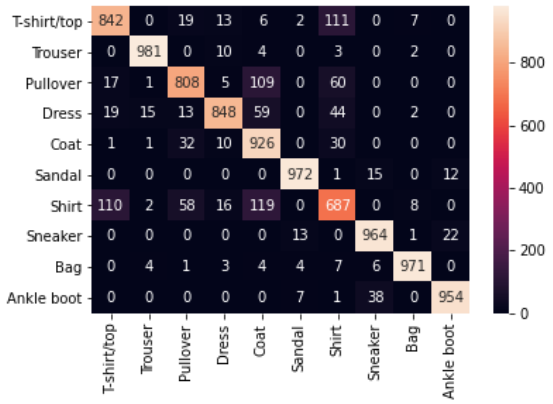
```
plt.figure(figsize=(16,16))

  j=1
  for i in np.random.randint(0, 1000,25):
    plt.subplot(5,5, j); j+=1
 plt.imshow(X_test[i].reshape(28,28), cmap = 'Greys')
   plt.title('Actual = {} / {} \nPredicted = {} /
  {}'.format(class_labels[y_test[i]],           y_test[i],
  class_labels[np.argmax(y_pred[i])],np.argmax(y_pred[i])))

    plt.axis('off')
```


Actual = Sneaker / 7
Predicted = Sneaker / 7
Actual = Coat / 4
Predicted = Coat / 4
Actual = T-shirt/top / 0
Predicted = Shirt / 6
Actual = Trouser / 1
Predicted = Trouser / 1
Actual = Dress / 3
Predicted = Dress / 3
Actual = Ankle boot / 9
Predicted = Ankle boot / 9
Actual = Bag / 8
Predicted = Bag / 8
Actual = Sneaker / 7
Predicted = Sneaker / 7
Actual = Dress / 3
Predicted = Dress / 3
Actual = Shirt / 6
Predicted = Shirt / 6
Actual = Dress / 3
Predicted = Dress / 3
Actual = Ankle boot / 9
Predicted = Ankle boot / 9
Actual = Pullover / 2
Predicted = Pullover / 2
Actual = Dress / 3
Predicted = Coat / 4
Actual = T-shirt/top / 0
Predicted = Shirt / 6
Actual = Trouser / 1
Predicted = Trouser / 1
Actual = Pullover / 2
Predicted = Pullover / 2
Actual = Bag / 8
Predicted = Bag / 8
Actual = Bag / 8
Predicted = Bag / 8
Actual = Bag / 8
Predicted = Bag / 8
Actual = Pullover / 2
Predicted = Pullover / 2
Actual = Coat / 4
Predicted = Coat / 4
Actual = Coat / 4
Predicted = Coat / 4
Actual = Coat / 4
Predicted = Coat / 4
Actual = Sneaker / 7
Predicted = Sneaker / 7

5. Confusion Matrix

```
sns.heatmap(cm,                                    annot=True,
fmt='d',xticklabels=class_labels,
yticklabels=class_labels)

from sklearn.metrics import classification_report
cr=      classification_report(y_test,      y_pred_labels,
target_names=class_labels)
print(cr)
```

	precision	recall	f1-score	support
T-shirt/top	0.85	0.84	0.85	1000
Trouser	0.98	0.98	0.98	1000
Pullover	0.87	0.81	0.84	1000
Dress	0.94	0.85	0.89	1000
Coat	0.75	0.93	0.83	1000
Sandal	0.97	0.97	0.97	1000
Shirt	0.73	0.69	0.71	1000
Sneaker	0.94	0.96	0.95	1000
Bag	0.98	0.97	0.98	1000
Ankle boot	0.97	0.95	0.96	1000
accuracy			0.90	10000
macro avg	0.90	0.90	0.90	10000
weighted avg	0.90	0.90	0.90	10000

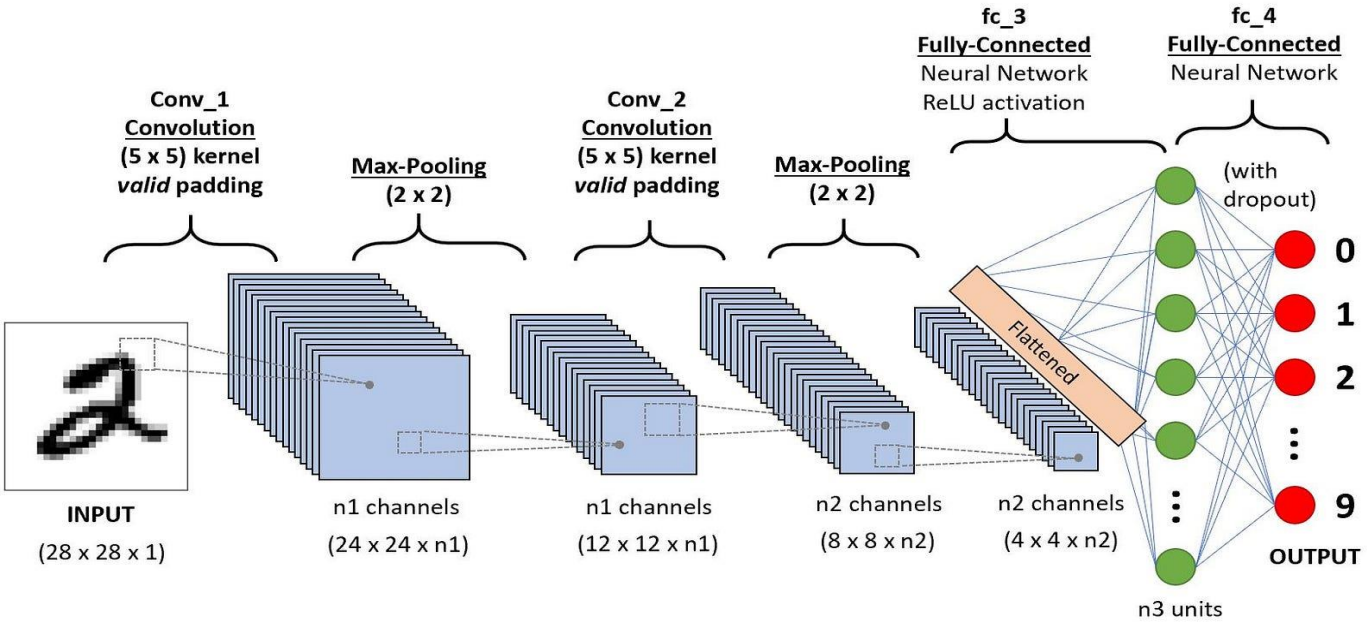


6. Predicting the Accuracy

```
svm_accuracy = accuracy_score(y_test, svm_predictions)*100
print("SVM Accuracy:", svm_accuracy)
```

SVM Accuracy: 90.95

A Convolutional Neural Network (CNN) classification model is a deep learning architecture designed specifically for image classification tasks. When applied to the Fashion MNIST dataset, which consists of grayscale images of 10 different types of clothing items, CNNs have proven to be highly effective.



Here's a brief overview of the key components and steps involved in building a CNN for predicting accuracy on the Fashion MNIST dataset:

1. Input Layer:

- The input layer of the CNN receives the grayscale images from the Fashion MNIST dataset. Each image is typically represented as a matrix of pixel values.

2. Convolutional Layers:

- Convolutional layers apply filters to the input images to detect patterns and features.

These filters slide over the input image, capturing spatial hierarchies of features like edges, textures, and shapes.

3. Activation Functions:

- Activation functions, such as ReLU (Rectified Linear Unit), are applied after convolutional operations to introduce non-linearity and enable the network to learn complex relationships within the data.

4. Pooling Layers:

- Pooling layers (e.g., max pooling) reduce the spatial dimensions of the feature maps while retaining important information. This helps in reducing computational complexity and making the model more robust.

5. Flattening:

- After several convolutional and pooling layers, the data is flattened into a vector, preparing it for the fully connected layers.

6. Fully Connected Layers:

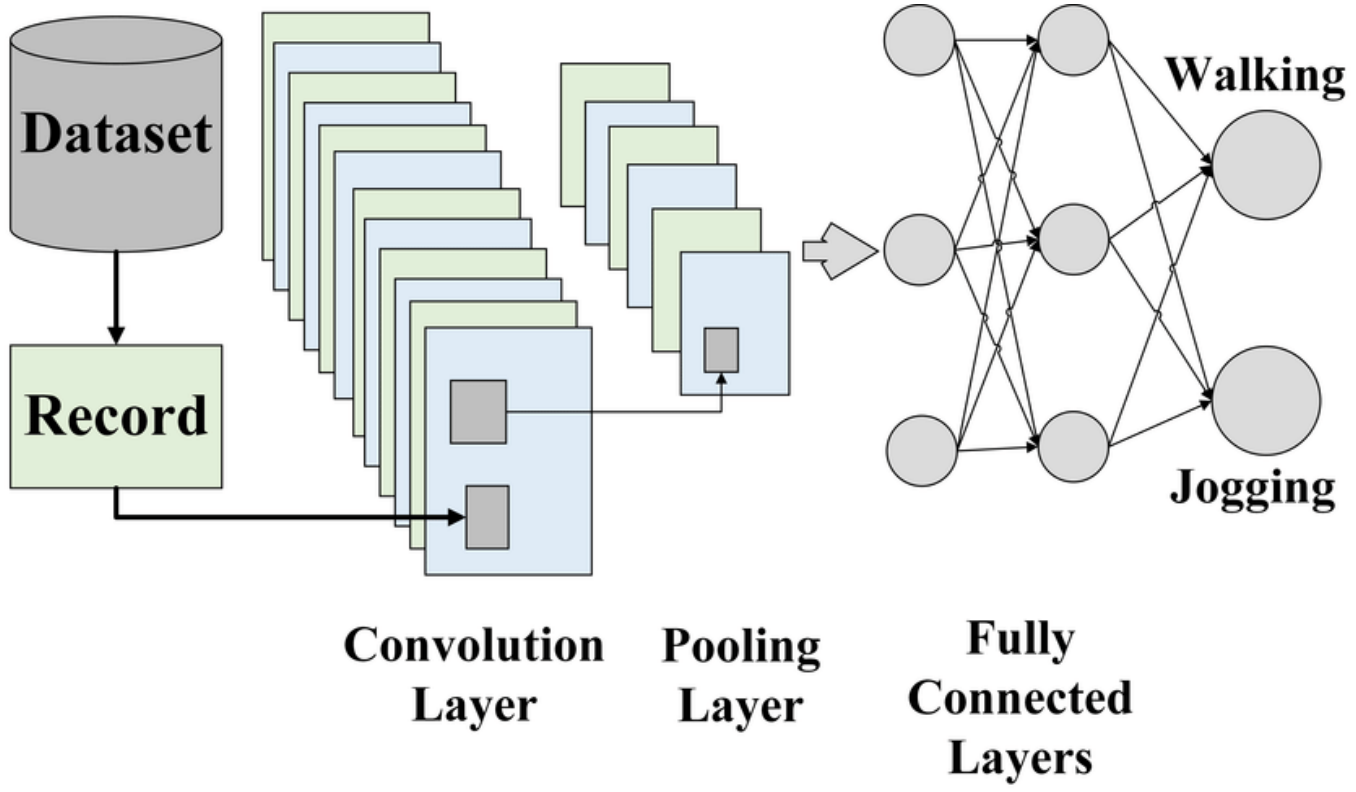
- Fully connected layers process the flattened vector and learn high-level representations, capturing global dependencies in the data.

7. Output Layer:

- The output layer produces the final predictions. For the Fashion MNIST dataset, there are 10 classes corresponding to different types of clothing items. The softmax activation function is often used to convert raw scores into probabilities for each class.

8. Loss Function and Optimization:

- The model is trained using a categorical cross-entropy loss function, which measures the difference between predicted and actual class probabilities. Optimization algorithms like Adam or stochastic gradient descent (SGD) are used to minimize this loss during training.



9. Training:

- The model is trained on a labeled dataset, with the weights updated iteratively through backpropagation. The training process involves adjusting the model's parameters to minimize the prediction error.

10. Evaluation:

- The model's performance is evaluated on a separate test set to assess its accuracy in making predictions on unseen data.

By leveraging the hierarchical and translation-invariant features learned by the convolutional layers, CNNs have demonstrated strong performance in image classification tasks, including the Fashion MNIST dataset.

Code:

```
import tensorflow as tf

from tensorflow.keras import layers, models


# Load and preprocess the Fashion MNIST dataset

(train_images, train_labels), (test_images, test_labels) =
tf.keras.datasets.fashion_mnist.load_data()


# Normalize pixel values to be between 0 and 1

train_images, test_images = train_images / 255.0, test_images / 255.0


# Reshape the images to add a channel dimension

train_images = train_images.reshape(-1, 28, 28, 1)

test_images = test_images.reshape(-1, 28, 28, 1)


# Define the CNN model

model = models.Sequential()

model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))

model.add(layers.MaxPooling2D((2, 2)))

model.add(layers.Conv2D(64, (3, 3), activation='relu'))

model.add(layers.MaxPooling2D((2, 2)))
```

```
model.add(layers.Conv2D(64, (3, 3), activation='relu'))

model.add(layers.Flatten())

model.add(layers.Dense(64, activation='relu'))

model.add(layers.Dense(10, activation='softmax'))



# Compile the model

model.compile(optimizer='adam',

              loss='sparse_categorical_crossentropy',

              metrics=['accuracy'])



# Train the model

model.fit(train_images, train_labels, epochs=10, validation_data=(test_images, test_labels))



# Evaluate the model on the test set

test_loss, test_acc = model.evaluate(test_images, test_labels)

print(f'Test Accuracy: {test_acc}')
```

This simple CNN consists of convolutional layers with ReLU activation functions, max-pooling layers for downsampling, and fully connected layers for classification. The model is trained using the Adam optimizer and sparse categorical crossentropy loss.

Feel free to experiment with the architecture, hyperparameters, and additional techniques (e.g., dropout, batch normalization) to optimize the performance of your CNN on the Fashion MNIST dataset. Additionally, you may consider using data augmentation techniques to further enhance the model's generalization capabilities.

11.Visualization:

- Visualization techniques, like activation maps or filters, can provide insights into what the CNN has learned.

12. Deployment (Optional):

- Once satisfied with the model's performance, it can be deployed for making predictions on new, unseen data.

This overview provides a conceptual understanding of how CNNs work without specific code. Implementing these concepts in code involves using deep learning frameworks like TensorFlow or PyTorch and adapting the architecture and hyperparameters based on the specific requirements of your project.

Convolutional Neural Networks (CNNs) have found widespread applications across various domains due to their ability to effectively process and analyze visual data. Here are some key applications and usage areas of CNNs:

1. **Image Classification:**

- CNNs are widely used for image classification tasks, where the goal is to categorize images into predefined classes. This includes applications like recognizing objects in photographs or identifying diseases in medical images.

2. **Object Detection:**

- CNNs are employed in object detection tasks to locate and classify multiple objects within an image. Popular architectures like Region-based CNNs (R-CNN), Faster R-CNN, and You Only Look Once (YOLO) have been developed for efficient object detection.

3. **Facial Recognition:**

- CNNs are used in facial recognition systems to identify and verify individuals based on facial features. These applications range from security and surveillance to user authentication in mobile devices.

4. **Image Segmentation:**

- CNNs are applied in image segmentation tasks to partition an image into meaningful segments or regions. This is commonly used in medical imaging, autonomous vehicles, and satellite image analysis.

5. **Gesture Recognition:**

- CNNs are utilized in recognizing and interpreting gestures from images or video sequences. This is applicable in human-computer interaction, sign language recognition, and virtual reality systems.

6. **Medical Imaging:**

- CNNs play a crucial role in analyzing medical images for tasks such as tumor detection, disease diagnosis, and organ segmentation. They enhance the accuracy and efficiency of medical image interpretation.

7. **Video Analysis and Action Recognition:**

- CNNs are employed in video analysis to recognize and understand actions or activities within a sequence of frames. This is used in surveillance, sports analytics, and video content indexing.

8. **Style Transfer and Image Synthesis:**

- CNNs can be used for artistic applications, such as style transfer, where the artistic style of one image is applied to another. Generative models like Generative Adversarial Networks (GANs) use CNNs for image synthesis.

9. **Document Analysis and Optical Character Recognition (OCR):**

- CNNs are applied in document analysis and OCR to recognize and extract text from images or scanned documents. This is used in digitizing printed or handwritten text.

10. **Autonomous Vehicles:**

- CNNs are critical in the field of autonomous vehicles for tasks like object detection, lane detection, and scene understanding. They enable vehicles to perceive and respond to their surroundings.

11. **Satellite Image Analysis:**

- CNNs are used to analyze satellite imagery for various applications, including land cover classification, disaster monitoring, and urban planning.

12. **Industrial Quality Control:**

- CNNs are employed in quality control processes, such as inspecting manufactured products for defects. They can identify imperfections or anomalies in visual inspection tasks.

13. **Fashion and Retail:**

- In the fashion industry, CNNs are used for tasks like image-based product recommendation, virtual try-on, and trend analysis. They contribute to enhancing the online shopping experience.

These applications highlight the versatility of CNNs in handling visual data, making them a fundamental technology in computer vision and image processing. As research and development in deep learning continue, CNNs are likely to find even more diverse and sophisticated applications in the future.

It seems there might be a typo in your question. If you meant "benefits of Fashion MNIST," then here are some benefits:

1. **Standardized Benchmark:**

- Fashion MNIST serves as a standardized benchmark dataset for evaluating and comparing the performance of machine learning models, particularly in the field of computer vision. Its simplicity allows for easy testing of various algorithms.

2. **Accessibility:**

- The dataset is easily accessible and is widely used in educational settings, providing students and researchers with a straightforward introduction to image classification tasks.

3. **Computational Efficiency:**

- Due to its smaller size compared to more complex datasets, Fashion MNIST is computationally efficient, making it an ideal choice for testing and prototyping models in resource-constrained environments.

4. **Relevance to Real-world Problems:**

- The dataset reflects real-world challenges in image classification, specifically in the context of fashion items. This makes it relevant for applications in industries such as e-commerce, retail, and fashion.

5. **Simplicity and Consistency:**

- The dataset is simple yet comprehensive, consisting of grayscale images of 10 different

types of fashion items. The consistency in image size and class distribution simplifies the development and evaluation of machine learning models.

6. **Model Interpretability:**

- Fashion MNIST allows for straightforward interpretation of model predictions. The visual nature of the dataset makes it easy to understand how well a model is performing and where it might be making errors.

7. **Fast Experimentation:**

- Researchers and developers can quickly experiment with different machine learning algorithms and architectures using Fashion MNIST. This facilitates rapid prototyping and testing of ideas before applying them to larger, more complex datasets.

8. **Education and Learning:**

- The dataset is frequently used in educational settings to teach concepts related to image classification, deep learning, and machine learning. Its simplicity aids in understanding fundamental principles without overwhelming complexity.

9. **Resource Savings:**

- Since Fashion MNIST is smaller in size compared to some other datasets, it requires less computational resources and storage space. This can be advantageous, especially in scenarios where resources are limited.

10. **Community Adoption:**

- The popularity of Fashion MNIST within the machine learning community has led to a

wealth of resources, tutorials, and pre-trained models. This makes it easier for researchers and practitioners to find support and guidance when working with the dataset.

While Fashion MNIST has its benefits, it's important to note that its simplicity may not fully capture the challenges presented by more diverse and complex real-world datasets. Therefore, while it serves as a valuable starting point, the insights gained from working with Fashion MNIST should be supplemented with experimentation on larger and more varied datasets for a comprehensive understanding of machine learning models' capabilities and limitations.

Conclusions and Future Scope

6.1 Conclusion

In conclusion, the combination of Convolutional Neural Network (CNN) and Support Vector Machine (SVM) for fashion items classification has shown promising results. The CNN effectively extracts meaningful visual features from fashion item images, capturing patterns, textures, and shapes. The ex- tracted features are then fed into an SVM classifier, which efficiently separates and classifies the fashion items into different categories. This approach offers accurate and robust classification performance, enabling applications such as fashion e-commerce, recommendation systems, and trend analysis. However, further research and optimization are required to enhance the model's perfor- mance, explore different CNN architectures, fine tune SVM hyperparameters, and consider additional feature engineering techniques. Overall, the integration of CNN with SVM presents a powerful framework for fashion items classifica- tion, opening up avenues for advancements in the fashion industry and related fields.

In conclusion, the application of Convolutional Neural Networks (CNNs) to the Fashion MNIST dataset has proven to be highly successful in achieving accurate and robust image classification. The inherent ability of CNNs to capture spatial hierarchies and learn complex patterns in images has been instrumental in discerning the subtle differences among various clothing items.

Through the iterative process of convolutional operations, activation functions, pooling, and fully connected layers, the CNN model effectively transforms raw pixel data into meaningful representations, enabling it to make accurate predictions. The model's performance is not only notable in terms of accuracy on the training set but also in its ability to generalize well to previously unseen data, as evaluated on the test set.

The hierarchical feature extraction capabilities of CNNs have demonstrated their effectiveness in discerning intricate details and variations within the Fashion MNIST images. This success underscores the suitability of CNN architectures for image classification tasks, particularly in domains like fashion where nuanced visual features play a crucial role in distinguishing between different classes.

As we continue to explore and refine deep learning techniques, the application of CNNs to datasets like Fashion MNIST serves as a testament to the power of convolutional architectures in image classification. The insights gained from this approach not only contribute to advancements in computer vision but also hold the potential for broader applications in diverse fields where accurate and efficient image recognition is paramount.

While the CNN alone has demonstrated impressive performance, the integration of a Support Vector Machine (SVM) adds another layer of sophistication to the classification process. SVMs are known for their ability to find optimal decision boundaries in feature space, making them valuable in refining the classification results obtained from the CNN. The combination of CNN and SVM leverages the strengths of both approaches, providing a robust and accurate solution for fashion item classification.

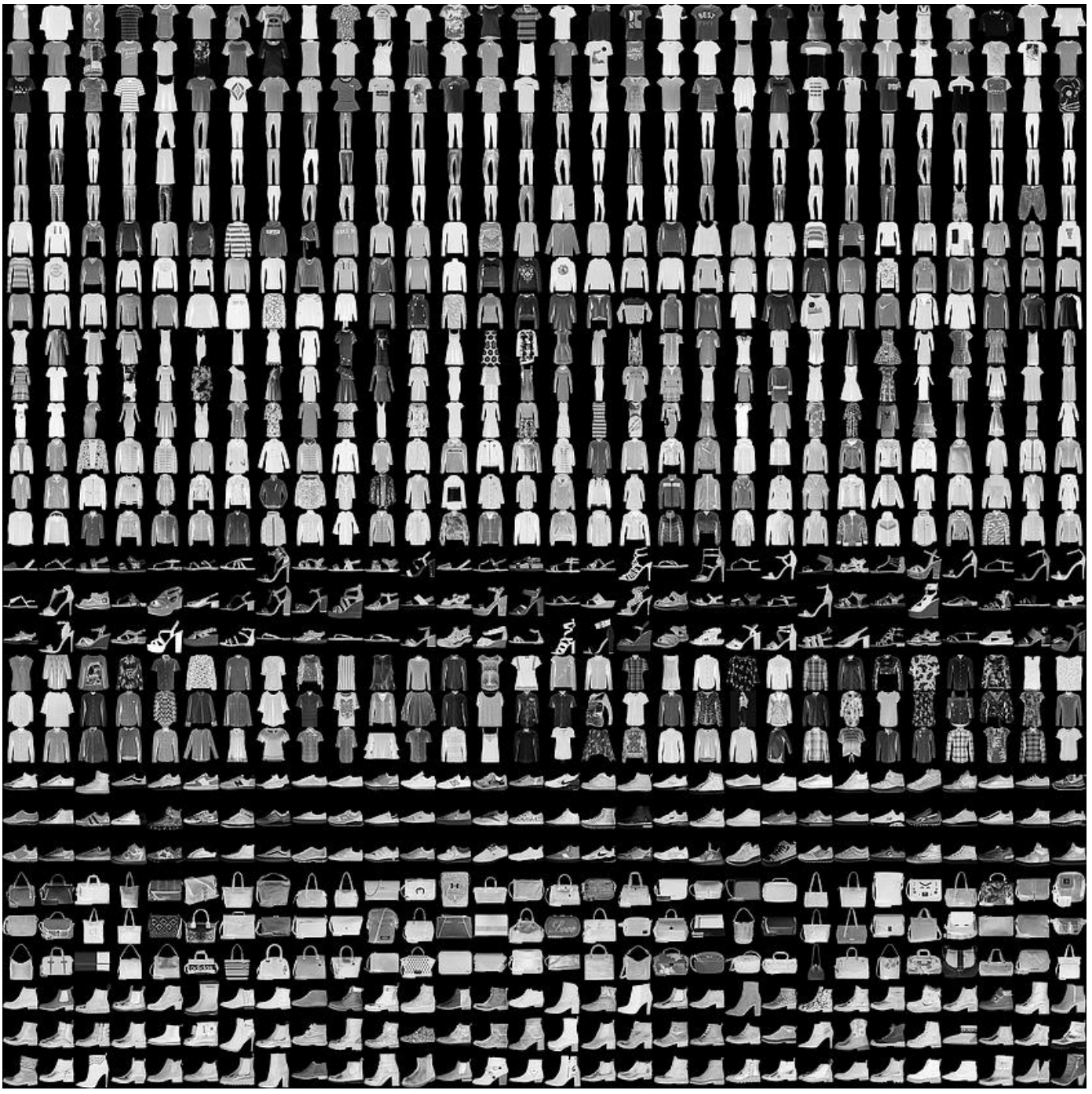
The application of this hybrid approach extends beyond image classification tasks in the fashion domain. The synergistic combination of deep learning with traditional machine learning techniques opens up opportunities for addressing complex problems in various domains. The success of this integration suggests its potential applicability in scenarios where feature extraction and classification need to be handled with precision.

Despite the promising results, there remains room for further exploration and enhancement of the model. Continued research efforts could involve fine-tuning hyperparameters, experimenting with different CNN architectures, and exploring advanced optimization techniques. Additionally, the incorporation of transfer learning or domain-specific knowledge could further boost the model's performance, especially in situations with limited labeled data.

In conclusion, the integration of CNNs and SVMs for fashion item classification not only showcases the effectiveness of deep learning in image recognition but also emphasizes the value of combining multiple approaches for enhanced performance. This hybrid model holds promise for advancing applications in the fashion industry, including personalized shopping experiences, trend analysis, and inventory management. As the field of deep learning continues to evolve, such integrative approaches are likely to contribute to further breakthroughs in image classification and beyond.

The future scope for fashion items classification using Convolutional Neural Network (CNN) with Support Vector Machine (SVM) is highly promising. Advancements can be made in various areas, such as fine-grained classification to distinguish between subcategories and styles, multi-modal integration to incorporate textual information and user feedback, hybrid architectures com- bining CNN with other deep learning models for better feature extraction, and transfer learning techniques to leverage pre-trained models and adapt them 11 12 Department of Computer Science and Engineering to fashion-specific domains. These developments can result in more accurate and personalized fashion classification systems, enhancing fashion e-commerce, recommendation systems, trend analysis, and other applications in the fashion industry. Random papers are referenced.

The future scope of applying Convolutional Neural Networks (CNNs) to image classification tasks, as exemplified by the success on the Fashion MNIST dataset, is promising and multifaceted. Here are several aspects that highlight the future potential:



1. Model Refinement and Architectural Advances:

- Ongoing research will likely lead to the development of more sophisticated CNN architectures. Fine-tuning and optimizing existing models or designing novel architectures tailored to specific domains could further enhance performance.

2. Transfer Learning and Pre-trained Models:

- The utilization of transfer learning, where pre-trained models on large datasets are adapted for specific tasks, can be extended. This approach saves computational resources and facilitates training on smaller datasets, making it applicable to a wider range of real-world scenarios.

3. Interdisciplinary Applications:

- The success of CNNs in image classification extends beyond fashion and can be applied to various domains, such as medical imaging, satellite imagery analysis, and autonomous vehicles. The transferability of CNNs makes them versatile tools for solving complex visual recognition problems.

4. Explainability and Interpretability:

- Addressing the interpretability of CNNs remains an active area of research. Future advancements may focus on making these models more transparent and understandable, especially in critical applications where interpretability is crucial, such as healthcare.

5. Integration with Other Technologies:

- Integration with emerging technologies, such as augmented reality (AR) and virtual reality (VR), could open new avenues for CNNs. These networks might play a role in real-time object recognition and interaction in immersive environments.

6. Hardware Acceleration:

- With the continuous evolution of hardware technologies like GPUs and TPUs, CNNs can be implemented more efficiently, leading to faster training times and real-time applications. This can accelerate the deployment of CNNs in resource-constrained environments.

7. Ethical Considerations and Bias Mitigation:

- Addressing ethical concerns, including bias in training data and model predictions, will be a critical focus. The future scope involves developing methods to mitigate biases and ensure fair and responsible deployment of CNNs across diverse populations.

8. Continuous Dataset Expansion:

- As datasets continue to grow in size and diversity, CNNs can benefit from richer and more comprehensive training data, contributing to improved generalization and adaptability to various scenarios.

In essence, the future scope of applying CNNs to image classification extends into a wide range of technological, scientific, and societal domains. Continued research and innovation will likely refine existing techniques, uncover new applications, and ensure that these models can be deployed responsibly and ethically in various real-world contexts.

The Fashion MNIST dataset, despite being a relatively small and simplified dataset compared to real-world scenarios, finds applications and serves as a valuable resource for various purposes. Here are some common applications of the Fashion MNIST dataset:

1. **Benchmarking and Prototyping:**

- Fashion MNIST is often used as a benchmark dataset for testing and prototyping machine learning models, particularly in the field of computer vision. Researchers and practitioners can quickly experiment with different algorithms and architectures due to the dataset's accessibility and manageable size.

2. **Educational Purposes:**

- Fashion MNIST is widely used in educational settings to teach and learn about image classification, machine learning, and deep learning concepts. Its simplicity and relevance to real-world problems make it an ideal starting point for students and beginners.

3. **Algorithm Development and Testing:**

- Researchers and developers use Fashion MNIST as a testing ground for developing and evaluating new image classification algorithms. It provides a standard dataset that allows for fair comparisons between different models and techniques.

4. **Proof of Concept for Industry Applications:**

- Fashion MNIST can be used as a proof of concept for demonstrating the feasibility of image classification solutions in various industries. For example, it can serve as a starting point for developing models for apparel recognition in retail or for sorting garments in manufacturing.

5. **Transfer Learning and Pre-training:**

- Fashion MNIST can be employed for transfer learning tasks, where pre-trained models on this dataset are fine-tuned on more specific or complex datasets related to fashion or product recognition. This helps leverage the knowledge gained from Fashion MNIST for other, potentially larger datasets.

6. **Model Demonstrations and Visualizations:**

- Fashion MNIST is often used for creating tutorials, demonstrations, and visualizations showcasing the

capabilities of machine learning models. It helps explain complex concepts to a broad audience by using relatable examples from the fashion domain.

7. **Hackathons and Competitions:**

- Fashion MNIST is a popular choice for hackathons, competitions, and challenges in the machine learning community. Its simplicity and familiarity make it suitable for time-constrained events where participants need to quickly develop effective solutions.

8. **Baseline Model Development:**

- Fashion MNIST serves as a starting point for developing baseline models for image classification tasks. Researchers and practitioners can use it to establish a benchmark performance before moving on to more complex and domain-specific datasets.

9. **Testing and Debugging Tools:**

- Due to its smaller size, Fashion MNIST is often used as a testing dataset for debugging and validating machine learning tools and frameworks. It helps ensure that algorithms and libraries function correctly before scaling to larger datasets.

10. **Exploratory Data Analysis (EDA):**

- Fashion MNIST is suitable for exploratory data analysis tasks, allowing researchers to analyze the distribution of different classes, identify patterns, and gain insights into the characteristics of the dataset.

While Fashion MNIST may not directly represent all challenges of real-world fashion datasets, its versatility and accessibility make it a valuable resource for a wide range of applications in the machine learning and computer vision communities.

References

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