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Comparison of Transferred Deep Neural Networks for Knit Fabric Texture Recognition and Classification

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Abstract: Texture of knitted fabrics is an important factor for better decision making concerning their use in the production of specific types of garments. Traditional manual visual inspection for recognizing knit fabric textures faces various challenges and can be inaccurate resulting in discontent with and waste of manufactured clothing. Automating the task using a deep learning-based image identification and classification approach is a viable solution to this challenge. For accurate results, building deep learning models and starting the learning process from scratch can be computationally expensive and time-consuming. Also, a rule of thumb for deep learning-based image classification is 1,000 representative images per class, which comes from the original ImageNet classification competition. In this paper, we propose transfer learning approach to recognize and classify 17 types of knit fabric texture images obtained using high resolution camera under proper lighting effects. This approach addresses both the issues related to building DL models from scratch as transfer learning uses pre-trained models that allow us to build accurate models in a timesaving way, and 1,000-image magic number goes down significantly when using such models. Three pre-trained models, Very Deep Convolutional Networks for Large-Scale Image Recognition (VGG-16), Inception-v3 and Residual net (ResNet50), are used for recognition and classification of images of 17 types of knit texture. Our models' outcomes were assessed using evaluation metrics such as accuracy, precision, recall, and F1-score. The experimental results showed that Inception-v3 achieved higher accuracy followed by ResNet50 and VGG-16.

***IndexTerms* - Knit Fabric Texture, Pattern Recognition, Image Classification, Deep Learning, ResNet-50, VGG-16, Inception-v3, Transfer Learning.**

I. INTRODUCTION

Knitted fabric are produced from one or more long interconnecting and looping strands, like how we would knit with knitting needles and a ball of yarn in the traditional way. Knit fabrics are a stretchy sort of fabric that is commonly used for casual wear garments, but they may also be utilised for a variety of other purposes. Knit textiles are created from a variety of fibres, including cotton, silk, viscose, spandex, wool, and polyester, and are used in the fashion industry for tee-shirts, sweaters, joggers, dresses, underwear, and swimwear. Knitted fabrics are usually broadly classified into weft knits and warp knits. In this study we have investigated 17 different types of knit fabrics namely Flat or Jersey Knit, Purl Knit, Rib Stitch Knit, Interlock Stitch Knit, Double Knit, Warp Knitted, Tricot Knit, Raschel Knit, Cable Knit, Bird's Eye Knit, Pointelle Knit, Intarsia Knit, Jacquard Knit, Knitted Terry, Knitted Velour, Sliver Knit and Fleece Knit. The texture of knitted fabric is critical factor for making better decisions about its use in the manufacturing of various types of garments. So, before the knit fabric is processed further in the apparel manufacturing process, it's texture must be recognised.

Knit fabric pattern recognition is now reliant on manual procedures including the use of human eyes augmented by technology such as a microscope or magnifying glass. Traditionally, a specialist performs this manual inspection, which necessitates knowledge and experience. However, it has various disadvantages, including considerable effort, inefficiency, wrong identification, and time-consuming, as well as subjective human factors, such as mental and physical tension, dizziness, and exhaustion, which all affect recognition results. As a result, developing an automated inspection system for the recognition of knit fabric patterns is critical in order to generate high-quality products that match client expectations. Computer Vision (CV) task of image classification using Deep Learning (DL) is a viable way for implementing this automated inspection system.

In the textile sector, machine learning (ML) tasks such as clustering, and classification are being used to solve a variety of problems where traditional methods are ineffective. The following is a list of some of the literature on ML in the textile sector, with a focus on knitted fabrics. Trunz et al. a method for identifying and localising the different types of stitches. These localised stitches were used to deduce the underlying grid-like structure of knitted fabric. Only knit and purl stitch types were used in their trials. The methods described above are reverse engineering-based fabric prototyping based on a single image. Yildiz et al. suggested a dimensionality reduction method based on principal component analysis for feature extraction and classification in faulty fleece fabric. He examined the accuracy of Naive Bayes and K-nearest neighbour classifiers and found that the latter was superior. This method only considered binary patterns, not complicated texture patterns. The fabric features were extracted using the local binary pattern (LBP) and gray-level co-occurrence matrix (GLCM), and the fabric textures were classified using the support vector machine (SVM) by Li et al. They combined LBP and GLCM, which increased recognition performance over feature extraction algorithms based on either of them separately. This approach relied solely on handcrafted elements, and its use on non-woven and knitted fabrics was untested. For the identification of woven fabric pattern, Xiao et al. employed transform invariant low-rank textures (TILT) and histogram of oriented gradients (HOG), as well as fuzzy c-means clustering (FCM) to distinguish the warp and weft cross points.

This study employs transfer learning approach that solves the challenges in training CNN models from scratch which include significant time consumption and need for large amount of data by using pre-trained CNN models. Data Augmentation is applied to the knitted fabric texture image dataset to further increase the amount of data for training the models. Three Convolutional Neural Network (CNN) based pre-trained models, VGG-16, ResNet-50 and Inception-v3, are used for recognition and classification of 17 types go knitted fabric texture images. A comparison between these 3 models based on. Evaluation metrics such as accuracy, precision, recall and F1 score shows that Inception-v3 provides highest accuracy among the three followed by ResNet-50 and VGG-16.

The remainder of this paper is organized as follows: In Section 2, we describe the framework of our proposed model, details of the dataset, data augmentation, along with the DCNN models used; in Section 3, we present our experimental results and performance metrics used; in Section 4 we present a discussion and comparison with other works; and finally, the conclusions are drawn in Section 5.

II. Knitted Fabric Textures

1. Jersey Knit - Fabrics with obvious flat vertical lines on the front and dominant horizontal ribs on the back are known as flat or Jersey Knit. The flat or jersey knit stitch is commonly used because it is quick, cheap, and can be altered to create fancy patterned fabrics. Regular flat knits tend to "run" if a yarn is split, which is a severe drawback. To make terry, velour, and plush fabrics, the flat or jersey stitch can be altered by using different yarns or double-looped stitches of different lengths. Nylon hosiery, men's underwear, and t-shirts are all made with this stitch.

Figure 1: Jersey Knit

2. Purl Knit - Purl Knit Fabrics have the same appearance on both sides. The purl stitch can be used to make a variety of appealing patterns and designs. Bulky sweaters and children's apparel are frequently made with it. Purl knits are known for their slow production speed. Purl Knit is created by knitting yarn in one wale of the fabric using alternate knit and purl stitches. Knit and purl stitches alternate in the fabric's design. The fabric is reversible and looks the same on both sides. The cloth is flat and does not curl. In the length direction, it is more strechy.

Figure 2: Purl Knit

3. Rib Stitch Knit - Stitching on the Rib Knits have stitches drawn on both sides of the cloth, resulting in wales columns on both the front and back. Rib stitch creates materials with a lot of flexibility. Rib knits are used to create the “ribbing” seen on the lower borders of sweaters, sleeve cuffs, and necklines. Knitting yarn as alternate knit and purl stitches in one course of the cloth creates rib-knit fabric. Knit and purl stitches alternate in the fabric's wales. It's a reversible fabric since it looks the same on both sides. Both flat and circular knitting machines can be used to make these.

Figure 3: Rib Stitch Knit

4. Interlock Stitch Knit - Interlock stitch knits are rib stitch knits with a twist. Interlocks have the same front and back. Unless finer yarns are utilized, these textiles are usually heavier and thicker than standard rib knit fabrics. Stitches are interlocked to prevent runs and make garment materials that don't ravel or curl at the edges.

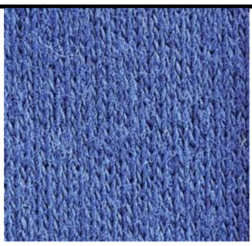
Figure 4: Interlock Stitch Knit

5. Double Knit - Interlock stitches and their variations are used to create double knits. Two sets of needles, positioned at an angle to each other, are used in the process. Polyester and wool are the most common fibres used in double knits. Weft knitted fabrics having two sets of needle beds are known as double knits. The structure of the cloth is more stable and compact. The textiles do not curl or ravel at the edges. They can be designed and textured in a variety of ways. To knit one course in the fabric, one or two yarns are utilized.


Figure 5: Double Knit

6. Warp Knit - Warp knitted fabrics are created with strands from the warp beam in a particular knitting machine. They are knitted from numerous threads, unlike weft knits, with yarns producing loops in adjacent wales. A pick glass can be used to identify the cloth. The fabric contains slightly inclined vertical knitting loops on the face side and inclined horizontal floats on the backside. They aren't prone to ravelling. Yarn loops are created in a vertical or warp direction to create warp knit fabrics. All the yarns used for a warp knit's width are placed parallel to each other, like how yarns are placed in weaving. Tricot and Raschel knits are commonly used to create high-quality fabrics with this technique.

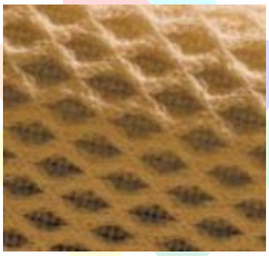
Figure 6: Warp Knit

7. Tricot Knit - Tricot knits are almost entirely made of filament yarns, which must have a consistent diameter and high quality in order to be used with the ultra-high-speed tricot knitting machines. Tricot knitting machine fabrics are typically plain or have a simple geometric design. The fabric has vertical wales on the front side and crosswise courses on the back side.

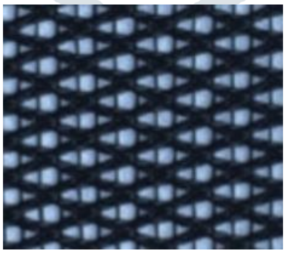
Figure 7: Tricot Knit

8. Raschel Knit - Raschel knits are made from various weights and types of spun or filament yarns. Intricate motifs, the open-space look of crochet or lace, and an almost three-dimensional surface effect design are all hallmarks of raschel knits.


Figure 8: Raschel Knit

9. Cable Knit - The loop transfer process is used to create cable fabric, which is a double-knit fabric. The fabric's wales have a rope-like look, and plaits are made by transferring loops between neighbouring wales. As the loops cross each other, the fabric produces a unique surface pattern that looks like braids. It's a popular fabric for sweaters.

Figure 9: Cable Knit

10. Bird’s Eye Knit - Bird's eye is a double-knit fabric with a tuck stitch and knitting stitch combination. The tuck stitch produces an eyelet or hole effect on the fabric surface that looks like a bird's eye. Fab The fabric is usually made up of a variety of coloured threads that create a scrambling effect. The fabric could be made with eyelet designs. They're a popular fabric for clothes, especially for women's wear.

Figure 10: Bird’s Eye Knit

11. Pointelle Knit - The fabric pointelle is a form of double knit. Miss stitches are patterned on the fabric. The fabric took on the appearance of lace, with holes created by the transferred stitches. The fabric's feminine appearance makes it excellent for women's tops and children's clothing.

Figure 11: Pointelle Knit

12. Intarsia Knit - Intarsia is a single knit cloth with a design. Knitting multi-coloured yarns are used to make it. The fabric is made up of the same course knitted in several colours and yarns. It has coloured graphics in the form of blocks that are dispersed across various colour backdrops. On both the front and back sides of the fabric, the patterns are identical. On the backside of the fabric, there are no floats. Shirts, blouses, and sweaters are commonly made from it.

Figure 12: Intarsia Knit

13. Jacquard Knit - Jacquard Jerseys are single jersey textiles manufactured with a Jacquard process on Circular Knitting machines. They're the most basic way to make patterned materials. They're made using unique patterns that could include any of the following: (1) Stitch combinations, or (2) Yarn type combinations in terms of colour, texture, and so on. Various coloured loops made of different threads run in the same direction on jacquard fabrics. Single jersey jacquards are known for their floats. In the sweater industry, they are commonly employed.

Figure 13: Jacquard Kint

14. Knitted Terry - Knitted Terry is a pile jersey fabric comparable to woven fabrics that is created with an unique attachment in standard circular knitting machines. The fabric's surface is covered in loops. The fabric is made up of two sets of yarns, one of which is used to form the pile and the other for the base fabric. Knit terry is more comfortable than woven terry because it is softer, more flexible, and comfier. They are not, however, as solid or as long-lasting as woven terry. It is extensively used in beachwear, towels, and bathrobes due to its softness and absorbency.

Figure 14: Knitted Terry

15. Knitted Velour - Knitted Velour fabrics have soft protruding fibres on the fabric surface and are Pile jersey fabrics. They, too, are made of an additional set of yarns that create pile loops on the fabric surface, like knit terry. These pile loops are sheared uniformly and brushed in Velour. It can be dyed and comes in a variety of solid colours. They're found in high-end garments including jackets, blouses, and gowns.

Figure 15: Knitted Velour

16. Sliver Knit - Pile jersey fabric makes up the Sliver Knit. In contrast to Velour fabric, Sliver knit fabric has a longer pile on the fabric surface. It's manufactured with sophisticated circular knitting machines that connect surface fibres that seem like fur to the cloth by knitting sliver along with the base yarn that makes the fabric. Compared to other pile jerseys, sliver knit fabrics have longer and thicker piles on the fabric surface. Imitation fur fabrics made of animal-printed sliver knit fabrics are very popular. They're more popular than fur because they're lighter, stretchier, and don't need specific storage. Jackets and coats are frequently made using them.

Figure 16: Silver Knit

17. Fleece Knit - Weft insertion jerseys are made of fleece. Weft insertion fabrics are knitted fabrics with an extra yarn introduced for each course. These extra yarns are retained in place by the loops in each cloth course rather than being knit. Decorative or functional yarn, such as stretch yarn, can be introduced. It gives support, protection, and comfort. In most cases, the insertion yarn is coarser than the foundation yarn. Fleece is what happens when the insertion yarns that make piles are sheared and napped. Cotton, Cotton/Polyester, Wool, and Acrylic are the most common materials used. Jackets, dresses, sportswear, and sweaters are examples of end uses.

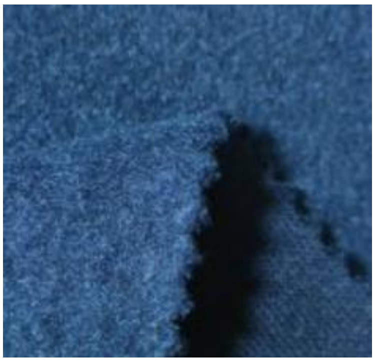

Figure 17: Fleece Knit

III. TRANSFER LEARNING

The introduction of Transfer Learning has accelerated the rapid advancements in Computer Vision and, by extension, image classification. Simply put, transfer learning allows us to leverage a pre-existing model that has been trained on a large dataset to solve our own problems. As a result, the cost of training new deep learning models is reduced, and we may be confident in the datasets' quality because they have been validated.

The following is the transfer learning model approach:
1. **Choose a CNN based pre-trained model.** From the available models, a pre-trained source model is picked.
2. **Model Reuse.** The pre-trained model can then be utilized to build a model for the second job of interest. Depending on the modelling technique employed, this may entail using all or sections of the model.
3. **Tune the model.** On the input-output pair data available for the job of interest, the model may need to be altered or refined.

Transfer Learning allows us to adapt knowledge of the pre-trained models from previously learned tasks to new tasks that are comparable. In context of this study, the task is image classification for which CNN based pre-trained models are used. The earliest blocks of CNN in the computer vision domain extract low-level information such as edges, forms, corners, intensity, and so on. as these initial blocks demand more processing power, this approach transfers the information (features, weights) of early blocks from a pre-trained network and uses it to categorize new images.

The CNN based pre-trained model used in this study are as follows:
1. Oxford VGG Model (VGG-16)
2. Google Inception Model (Inception-v3)
3. Microsoft ResNet Model (ResNet-50)

VGG-16 Architecture

The network's input is a two-dimensional image (224, 224, 3). The first two layers have the same padding and 64 channels of 3*3 filter size. Then, after a stride (2, 2) max pool layer, two layers of convolution layers of 256 filter size and filter size (3, 3). This is followed by a stride (2, 2) max pooling layer, which is the same as the previous layer. Following that, there are two convolution layers with filter sizes of 3 and 3 and a 256 filter. Following that, there are two sets of three convolution layers, as well as a max pool layer. Each has 512 filters of the same size (3, 3) and padding. This image is then fed into a two-layer convolution stack. The filters utilized in these convolution and max pooling layers are 3*3 instead of 11*11 in AlexNet and 7*7 in ZF-Net. It also employs 1*1 pixels in some of the layers to adjust the amount of input channels. After each convolution layer, a 1-pixel padding (same padding) is applied to avoid the image's spatial information from being lost. The (7, 7, 512) feature map is got after stacking the convolution and max-pooling layers. This output is flattened to make a (1, 25088) feature vector. Following that, there are three fully connected layers: the first takes input from the last feature vector and outputs a (1, 4096) vector, the second layer also outputs a (1, 4096) vector, but the third layer outputs 1000 channels, and the output of the third fully connected layer is then passed to the SoftMax layer to normalize the classification vector. Top-5 categories for review after the classification vector output. The activation function for all hidden layers is ReLU.

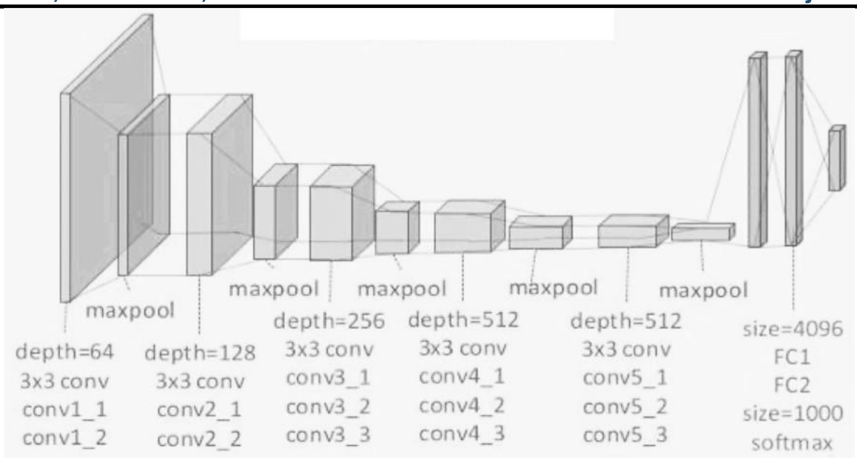

Figure 18: VGG-16 architecture

ResNet-50 Architecture

ResNet50 is a ResNet variation of 48 Convolution layers, 1 MaxPool layer, and 1 Average Pool layer. There are 3.8 x 109 floating point operations in it. The network is made up of one layer and a convolution with a kernel size of 7 * 7 and 64 distinct kernels, all with a stride of size 2. Then there's max pooling, which has a stride size of two. Following there is a 1 * 1,64 kernel, followed by a 3 * 3,64 kernel, and finally a 1 * 1,256 kernel. These three layers are repeated three times, for a total of nine layers in this step. Following there is a kernel of 1 * 1,128 followed by a kernel of 3*3,128 and finally a kernel of 1 * 1,512. This phase is performed four times, giving a total of 12 layers. Then there's a 1 * 1,256 kernel, followed by 3 * 3,256 and 1 * 1,1024 kernels, which are repeated six times for a total of 18 layers. Then a 1 * 1,512 kernel is added, followed by two more 3 * 3,512 and 1 * 1,2048 kernels, for a total of nine layers. After that, an average pool is run and finished with a fully linked layer with 1000 nodes, followed by a softmax function, giving one layer.

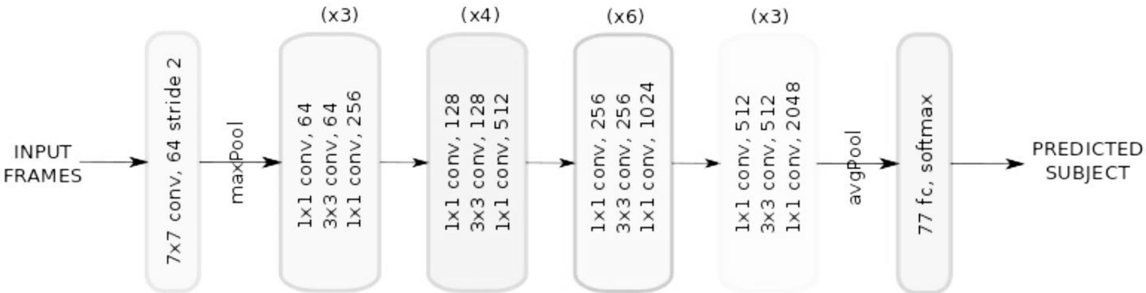

Figure 19: ResNet-50 architecture

Inception-v3 Architecture

Inception-v3 has three types of Inception modules, as indicated in Figure: Inception A, Inception B, and Inception C, from left to right. In Figure each Inception module is composed of several convolutional layers and pooling layers. Pool denotes a pooling layer, and n × m denotes a convolutional layer, where n and m specify the dimensions of the convolutions. The Inception modules are well-designed convolution modules that can produce discriminatory features while also reducing the number of parameters. Each Inception module is made up of numerous convolutional and pooling layers in parallel. The Inception modules use small convolutional layers, such as 3 x 3, 1 x 3, 3 x 1, and 1 x 1, to decrease the number of parameters. Three Inception A modules, five Inception B modules, and two Inception C modules are stacked in sequence in Inception-v3. Inception-v3's default input image size is 299 x 299 pixels. The output of the original Inception-v3 network contains 1,000 classes.

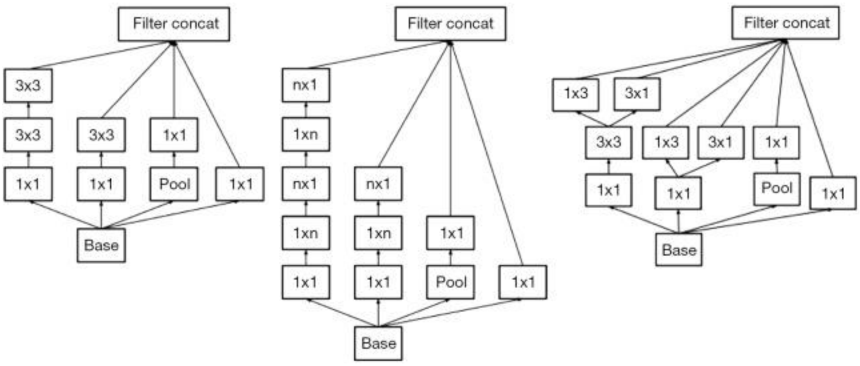

Figure 20: The Inception modules of Inception-v3: Inception modules A, B and C (from left to right)

IV. METHODOLOGY

Data Acquisition and Dataset

The knit fabric samples were sourced from a variety of places, including the lab, professors and students in the Fashion and Apparel Design (FAD) department, warehouses, and textile factories. As shown in Figure, the knitted fabric texture images were captured with a digital camera, the Canon PowerShot SX430 IS 20MP Digital Camera, which was surrounded by a light source to adjust the lighting illumination conditions. We captured 850 images covering all 17 types of knitted fabric textures. Out of these 850 images, we kept 170 images for our testing dataset, while the remaining 680 images were applied through various techniques of data augmentation to generate a total of 6120 training samples. These were subdivided into 17 classes, namely Flat or Jersey Knit, Purl Knit, Rib Stitch Knit, Interlock Stitch Knit, Double Knit, Warp Knitted, Tricot Knit, Raschel Knit, Cable Knit, Bird's Eye Knit, Pointelle Knit, Intarsia Knit, Jacquard Knit, Knitted Terry, Knitted Velour, Sliver Knit and Fleece Knit.

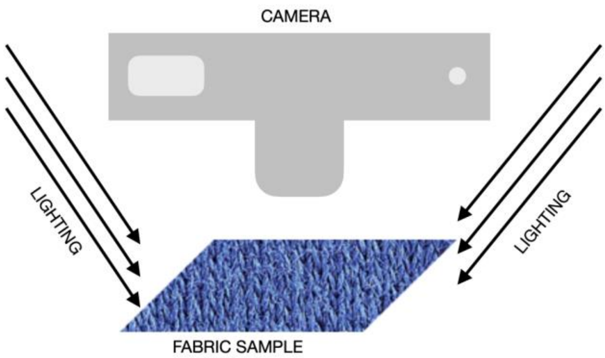

Figure 21: Knitted fabric texture image acquisition system

Data Augmentation

The problem of a training dataset that is too small has been handled utilizing data augmentation techniques [31]. Several data augmentation techniques are applied to the entire dataset, such as changing brightness or contrast, rotation, scaling, cropping, and flipping, to create a series of new images, thereby increasing the dataset. Data augmentation is a type of regularization that is applied to the entire dataset, which decreases the problem of overfitting. Figure shows a representation of these augmented images.

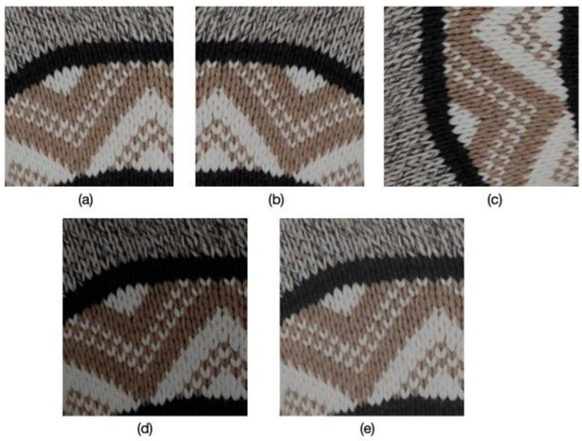

Figure 22: Some of the augmentation techniques applied to knit texture images. (a) Original image, (b) Flip, (c) Rotate, (d) Change in exposure and (e) Change in contrast

Proposed Pipeline Approach

The stages of the proposed pipeline-based approach (see Figure 23) are as follows:

1. **Image Acquisition -** Images of knitted fabric textures are collected from various sources. Each image is labelled with the type of texture it contains, to form a dataset. To build a dataset, each image is labelled with the type of texture it possesses.
2. **Preprocessing -** The images in the dataset needed to be converted, resized, and preprocessed appropriately. The dataset is then divided into training set and test set.
3. **Data Augmentation -** The training dataset has lower number of images. As a result, multiple augmentation approaches were applied on each image in the training dataset to increase its size, allowing the model to have improved generalization and recognition.
4. **Model Generation and Training -** Three models were built for this study. The first model was created with VGG-16 as the base, the second with ResNet-50, and the third with Inception-v3. During training, the algorithm optimized the parameters (update weights and biases) that were used for recognition.
5. **Model Testing and Evaluation -** On the test dataset, each trained model was tested for knit texture recognition and classification. The models' performance was assessed using evaluation metrics such as accuracy, precision, recall, and F1 score.

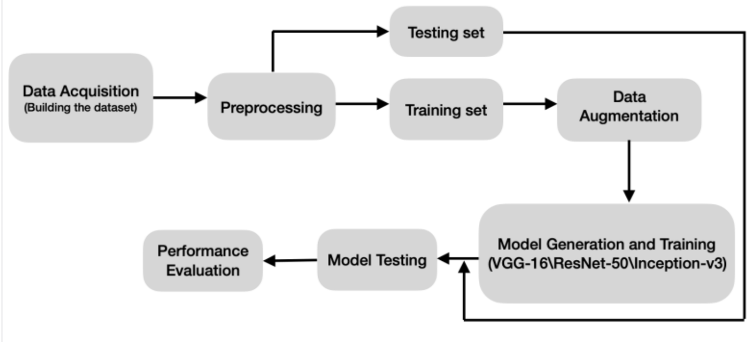

Figure 23: Stages of the proposed pipeline-based approach

V. Experimental Framework

In this work, we employed transfer learning approach, used three pre-trained CNN architectures, VGG-16, ResNet-50, Inception-v3, using the weights learned from training on ImageNet dataset. For VGG-16 and ResNet-50 based models, the knitted fabric texture images were resized to 224 x 224 dimensions, and for Inception-v3, to 299 x 299 dimensions. To feed the images into the model, the images were also pre-processed by subtracting the mean red-green-blue (RGB) value from each pixel. In comparison to its counterpart "random initialisation of weights," the pre-trained weights were utilised to avoid the model's poor initialisation. The fully connected layer, which was the last layer to classify images into ImageNet classes, was eliminated, and the pre-trained model's early convolutional layers served as the foundation for the new customised architecture. After that, a global average pooling layer was built on top of the base network, followed by two pairs of batch normalisation, fully connected, and dropout layers. There were 512 and 256 neurons in each of the two fully connected layers. A ReLU activation layer was placed after each fully connected layer. The pre-trained model's training time was reduced because of the batch normalisation layers. The presence of global average pooling and dropout layers mitigated the problem of overfitting. The model's performance was improved by adding dropout layers, which randomly removed redundant neurons. The problem of overfitting in deep architectures frequently fails to have a successful generalisation on data that has never been seen before (test data). Finally, the suggested model's final layer classified the knitted fabric texture images into 17 classes using the SoftMax activation function. Figure depicts the overall outline of the customised deep learning model.

The knitted fabric texture dataset created in this study was used to train the pre-trained models. Only the customised newly added layers attached to the base network were trained under this architecture, leaving the initial convolutional layers fixed. The primary goal of freezing these layers was to promote convergence and avoid gradient explosion throughout the training phase. Following the extraction of textural features, classification was used to compare the anticipated class to the actual class. The network's computation cost was reduced during training since the total trainable parameters of the customised CNN model were also reduced. For parameter optimization, the suggested model uses a stochastic optimization approach called Adam optimizer. The learning rate was set to 0.0001. Dropout ratios of 0.50 were chosen for both dropout layers. A batch size of 32 was chosen.

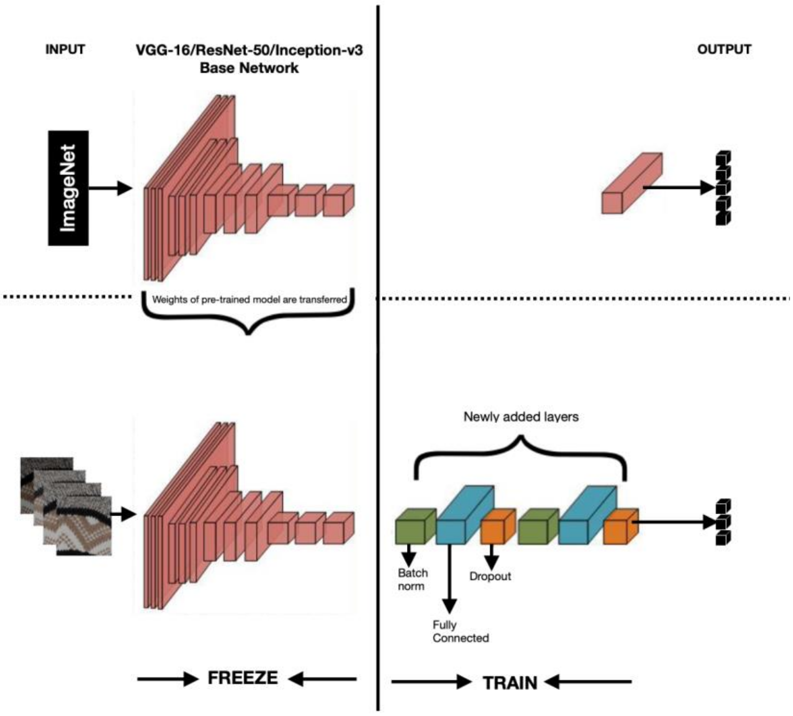

Figure 24: Framework of the proposed model

VI. Experimental Results

The NVIDIA Tesla T4 GPU, which is accessible in Google Colab, was used to train the models. Python 3.7 was used to implement the models, using Keras library and TensorFlow.

The results of three pre-trained CNN models, VGG-16, ResNet-50, and Inception-v3, were evaluated in this study using evaluation metrics such as accuracy, precision, recall and F1 score. The performance of the models is compared using these scores (see Table 1). The Inception-v3 based model outperformed the ResNet-50 and VGG-16 based models, as shown in Table. Inception-v3 outperforms ResNet-50 by a little margin, however there is a considerable difference in performance between VGG-16 and Inception-v3 in terms of accuracy and other evaluation metrics. The most likely reason for this is that the VGGNet has a larger number of trainable parameters (134M) and lacks the skip connections that make computations easier.

MODEL	ACCURACY	PRECISION	RECALL	F1 SCORE
VGG-16	0.864	0.858	0.863	0.860
ResNet-50	0.933	0.923	0.931	0.926
Inception-v3	0.952	0.940	0.950	0.947

Table 1: Performance comparison of VGG-16, ResNet-50 and Inception-v3 based models using evaluation metrics.

As seen in Table 1, we can conclude that among the 3 models implemented for knitted fabric texture recognition and classification, Inception-v3 based model provides best results followed by ResNet-50 and VGG-16.

VII. Discussion

Researchers have proposed methods based on traditional machine learning techniques employing handmade features in prior studies, however these methods are time-consuming and require big datasets. Both issues are addressed and resolved in our suggested transfer learning approach. Using pre-trained models saves time and considerably decreases the quantity of data needed to train the models. Inception-v3 outperformed ResNet-50 and VGG-16 in recognizing and classifying 17 different types of knitted fabric texture photos, as indicated in the Table 1. The images in the dataset show several variations, yet the Inception-v3 model can handle them and learn the high-level descriptive characteristics. As a result, the model demonstrates its versatility by outperforming other approaches in handling the intricacy contained in knitted fabric images. Additionally, the data augmentation approaches boosted the diversity of the available data, which improved the model's overall performance. The following three primary characteristics are reflected in the better recognition and classification accuracy: 1. When physical properties vary, the model remains robust. 2. Using the transfer learning technique, we may train the model with fewer parameters, making it more computationally efficient. 3. The proposed model does not rely on handcrafted features, instead performing feature extraction and classification in a fully automated end-to-end architecture. Our work can be expanded in the future to recognize and classify various forms of fabric, such as non-woven and woven fabrics.

VIII. Conclusion

Our paper proposes a transfer learning approach to recognize and classify 17 types of knit fabric texture images using pre-trained models like VGG-16, Inception-v3, and ResNet50. The motivation for this work is to address challenges related to traditional manual visual inspection of knit fabric textures, which can be inaccurate and result in wasted manufactured clothing. By using pre-trained models, the computational cost and time required to build accurate models from scratch is reduced. Our results show that Inception-v3 achieved the highest accuracy, followed by ResNet50 and VGG-16, which were evaluated using metrics such as accuracy, precision, recall, and F1-score.

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