international DESIGN JOURNAL
Print ISSN 2090-9632
Online ISSN 2090-9640

FabricNet: Multi-Task Deep Learning with CNN for Classification of Woven Fabric Structures and Density Estimation

Prof. Mohamed Elsaied Dorgham
Professor of textile machinery, Weaving and Spinning Department, Faculty of Applied Art, Helwan University, ms.dorgham@a-arthellwan.com.eg

Abeer A Dawoud
Department of Weaving and Spinning, Faculty of Applied Arts, Helwan University, Egypt, abeerdawoud@a-arts.helwan.edu.eg

Dr. Hany S ELnashar
Faculty of Computers and Artificial Intelligence, Beni-Suef University, Benisuef, 62511, Egypt, hsoliman@bsu.edu.eg

Dr. Shaymaa G Abdelrazek
Textile equipment, Facuty of Industry and Energy Technology, 6th of October Technological University, Giza, Egypt
Textile Engineer, Faculty of Applied Arts, Helwan university, Egypt, ahmedshaymaa00@gmail.com

Abstract

The textile industry has undergone a transformation thanks to artificial intelligence (AI), which has changed quality control, design, and production. Artificial intelligence (AI) powered tools and algorithms enhance a variety of industrial processes, including supply chain management, manufacturing, fabric design, and pattern development. Machine learning algorithms evaluate large data sets to identify trends, forecast demand, and enhance inventory control all of which result in more efficient and cost-effective operations. Artificial Intelligence (AI) can reverse engineer the manufacturing process, identify required materials and components, and evaluate the structure and characteristics of textiles. Artificial Intelligence (AI) methods such as computer vision, deep learning, and machine learning can be applied to analyze photos, videos, and other sorts of data in order to extract useful information about textiles. Due to manual visual inspection, woven fabric classification and warp and weft thread density counts have historically been extremely difficult. Additionally, early machine learning-based techniques rely solely on labor-intensive and prone to errors manual characteristics. To increase production, an automated system that integrates warp and weft thread counting with woven fabric classification is required, so this paper presents multi-task deep learning model for warp and weft thread counting, as well as classification and recognition of woven fabrics structure, based on data augmentation and transfer learning techniques. The results of the model were evaluated using evaluation metrics such as accuracy, classification loss for fabric classification and regression (mean absolute error) for warp and weft densities.

Keywords

fabric classification, warp and weft density, deep learning, CNN, woven fabric

Paper received June 20, 2025, Accepted August 31, 2025, Published online November 1, 2025

Introduction:

Currently, artificial intelligence is one of the most exciting and broadly useful areas of computer science. Artificial intelligence is evolving when a machine can think, hear, and solve problems. The goal of artificial intelligence is to build a computer that can think for itself. Learning, perception, problem-solving, thinking, and language are some of the components that make up intelligence. (1)

One of the industries that most effects people's quality of life globally is the textile sector. fabric is one of the essentials of human existence. One of the most crucial strategies the textile industry uses to stay competitive in the market is innovation. New methods, the use of computer intelligence, and the creation of sustainable materials are becoming increasingly common in the fields of fashion, sports, uniforms, and products. The technological development of textiles has resulted in significant capabilities that could differentiate them in this type of business. The entire textile and clothing manufacturing process has been updated, from raw

CITATION **Mohamed Dorgham, et al (2025), FabricNet: Multi-Task Deep Learning with CNN for Classification of Woven Fabric Structures and Density Estimation, International Design Journal, Vol. 15 No. 6, (November 2025) pp 107-115**

material selection to production methods. [2,3]
Reverse engineering is particularly useful in the textile sector, where understanding fabric compositions and structures improves product repeatability and quality. Reverse engineering using AI not only speeds up these processes but also enables automation, reducing the need for manual inspection and facilitating accurate analysis of textile patterns, fiber properties, and material quality. [4,5]

One of humanity's oldest inventions, fabric has developed from hand woven textiles to contemporary machine-based electronic textiles. Because of its structure and appearance, the weave pattern the most crucial component of woven fabrics plays a major role in design and redesign as well as textural analysis in the textile manufacturing business.(6) In the production process, it is crucial to recognize the pattern of the woven cloth before weaving machines proceed with additional processing. Currently, woven fabric pattern identification is mostly done by hand with the use of human eyes and tools like a magnifying glass or microscope. This manual check is often carried out by a specialist who needs training and experience. However, it has a number of disadvantages, including labor-intensive, inefficient, and time-consuming, as well as subjective human factors, such physical and mental stress, fatigue, and dizziness, which eventually impact the recognition results. Therefore, in order to create high-quality products that satisfy customers, an automated inspection system for the recognition of woven fabric patterns must be developed. [7,8]

Fabric pattern recognition has gained increasing interest in recent years, with methods classified into statistical methods such as texture and database/model methods. Statistical texture methods use pre-processed images to extract information about fabric structure, while database/model methods use algorithms to identify and match fabric weaving patterns. However, recognition accuracy and performance depend on the size of the database. Examples include photometric differential analysis, adaptive mesh models, and backpropagation neural networks. (9,10) The techniques for identifying woven fabric have a number of drawbacks. The database of woven fabric photographs was not widely available. The extraction of texture features during image acquisition was directly impacted by the fabric's rotational fluctuations. Uncertain texture images could be the result of the bad lighting effect. Deep learning is a powerful tool for recognizing fabric structure and threads density, relying on intelligent models to accurately distinguish patterns and threads. These technologies also help detect textile defects such as distortions or damage, improving manufacturing and inspection quality. [11]

One kind of deep learning technique that is frequently used to examine and extract visual characteristics from vast volumes of data is the convolutional neural network (CNN). CNNs can be utilized for a variety of AI activities, such as recommendation engines and natural language processing, even though their primary use is in image-related applications. Large volumes of data are ingested and processed in a grid format by convolutional neural networks, which subsequently extract crucial granular features for detection and classification. Convolutional, pooling, and fully connected layers are the three main types of layers found in CNNs. Every layer has a distinct function, works with ingested data, and gains complexity over time. [12]

2- Materials and methods:

This research's primary goal is to demonstrate how artificial intelligence techniques can be used to reverse the engineering of the textile industry. Specifically, it explains how to determine the fabric weave structure of textiles as well as the density/cm of the warp and weft threads. Convolutional Neural Networks (CNN) (deep learning) multi-task model created and trained**.** A model is a learning algorithm that predicts an output "Y" after taking input data "X" and transforming it into target attributes. For testing and training, a CNN model is constructed. CNN uses convolutions to identify patterns in the pictures. A sizable ImageNet dataset is used to train the suggested CNN model. It picks up simple patterns like dots, yarns, edges, and diagonals in the first few layers. Later layers combine these simple patterns to create more intricate ones.

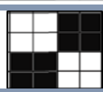
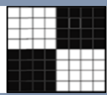
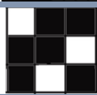
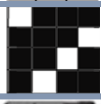
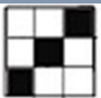
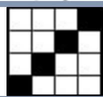
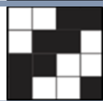
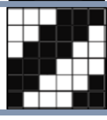
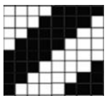
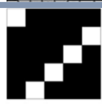
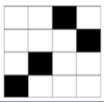
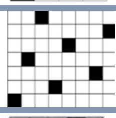
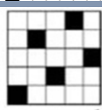
2.1 Data Acquisition:

To create the dataset, the research samples were gathered from the local Egyptian market. 330 samples with various fabric weave structures and materials including natural, synthetic, and blended materials used in the study. The warp and weft densities/cm of these samples vary. Different fabric weave structures or densities/cm are used to examine how they affect model evaluation.

2.2 Samples specifications:

The specifications of the gathered samples, including fabric weave structure, are shown in table (1). The warp and weft densities of these samples vary.

Table (1) The collected samples specifications

Number of samples	Fabric weave structure		Design of fabric weave structure
246	Structure of plain weave and its derivatives	Plain weave 1/1	
2		Weft Rip 2/2	
1		weft Rip 3/3	
11		Matt weave 2/2	
11		Matt weave 4/4	
14	Structure of twill weave	Twill 2/1	
3		Twill 3/1	
7		Twill 1/2	
6		Twill 1/3	
19		Twill 2/2	
1		Twill 3/3	
3		Twill 4/4	
1		Twill 4/1	
2	Structure of satin	Satin 4	
1		satin 7	
2		satin 5	
230	Total samples		

2.3 Dataset:

In many fields, such as statistics, data science, machine learning, and artificial intelligence, a data set is a collection of data used for analysis, training, or testing. Usually, tables are used to gather information.

The digital image of the fabric, the object being evaluated, is the most important part of our work in this study. Every effort must be made to use high-quality images. This feature facilitates accurate feature extraction, which enhances the analysis phase. The iPhone 12 Pro Max mobile camera, which has the following specifications: MP, f/1.6 aperture, and pixel size of 1.7 µm, was used to shoot the textile photos. As seen in figures 1, 2and 3the camera was positioned above a cloth lens that could magnify images ten times. A number of textile factories and warehouses provided samples of the woven fabric. We photographed 330 pieces of fabric in different settings, totaling 1000 images. 330 of these 1000 images were chosen for our testing dataset, while the remaining 670 images underwent various data augmentation techniques to yield a total of 3960 training samples. The area from the fabric samples that was shot measures 1 cm by 1 cm.

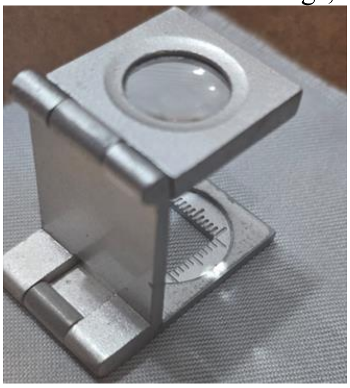


Figure (1) 10x Magnifying Textile Lens

Figure (2) iPhone camera above the lens to take a picture of the fabric

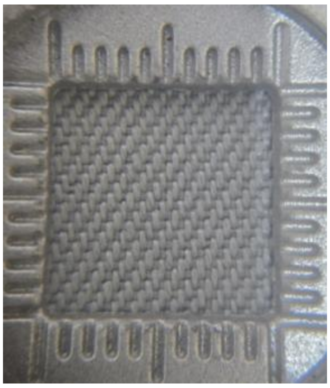


Figure (3) Fabric sample image taken

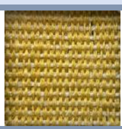
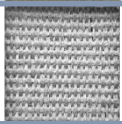
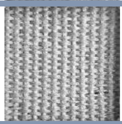
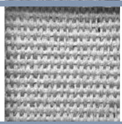
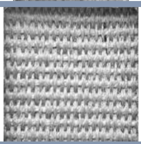
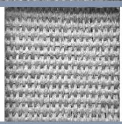
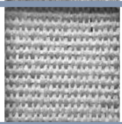
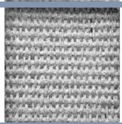
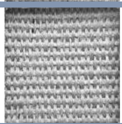
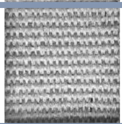
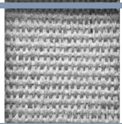
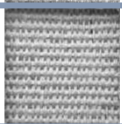
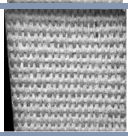
2.4 Data Augmentation:

By increasing the dataset's total number of images without changing the model's structure, data augmentation improves model performance in computer vision, machine learning, and natural language processing by increasing the volume and diversity of training data without the need for new data. This research utilized Photoshop for data augmentation on 330 fabric samples, applying various techniques on original photo. Samples were coded according to the method applied to the original images shown in table 2. Table 3 shows the technique applied to the original image of the first sample **(**SA1) and it was similarly applied to all 330 research samples, so that the total number of sample images became 12 images from each sample. Accordingly, the total number of images from 330 samples became 3960 images.

Table (2) Sample image coding method

The technique applied to the original image from photoshop	Image code according to the technique
SAMPLE 1 Preprocessing	SA1PRE
SAMPLE 1 Rotation 90	SA1R90
SAMPLE 1 Crop.vertical	SA1CRV
SAMPLE 1 Crop. Width	SA1CRW
SAMPLE 1 Sharp	SA1SHARP
SAMPLE 1 Facet	SA1FACET
SAMPLE 1 Grain	SA1GRAIN
SAMPLE 1 Flip Horizntal	SA1FLH
SAMPLE 1 Flip Vertical	SA1FLV
SAMPLE 1Noise	SA1+NOISE
SAMPLE 1 Blur	SA1BLUR
SAMPLE 1 Shear	SA1SHEAR

Table (3) Applied several augmentation techniques on the first sample (SA1) Plain weave 1/1

Sample code	sample pictures	Number of warp yarns /cm (Longitudinal yarns)	Number of weft yarns/ cm (Horizontal yarns)	Weave structure of samples design	Name of fabric weave structure
ORIGINAL SA 1		37	13		Plain weave 1/1
SA1PRE		37	13		
SA1R90		13	37		
SA1CRV		35	13		
SA1CRW		37	11		
SA1SHAR P		37	13		
SA1FACET		37	13		Plain weave 1/1
SA1GRAIN		37	13		
SA1FLH		37	13		
SA1FLV		37	13		
SA1+NOIS E		37	13		
SA1BLUR		37	13		
SA1SHEA R		37	13		

2.5 Importing Libraries:

The next step is to import the libraries required to process the data and create the model after finishing the dataset preparation (folder organization, image formatting, and readiness checks). After preparing the data for actual work, the first programming step is to import libraries.

At this stage, the programs that we will use to build and train the model are determined, such as: Jupyter Notebook to write and execute codes easily. Instead of starting from scratch and expending considerable effort, these libraries allow you to integrate prewritten code written by other programmers into this research. These libraries have been imported to develop AI and machine learning models.:

1- Cv2: To process images using OpenCV.
2- Numpy: To perform mathematical operations on matrices.
3- Pandas: To analyze data and load CSV files.
4- Tensorflow.keras: To create a deep neural network model using TensorFlow.
5- Sklearn.model_selection: To split data into training and test sets.
6- Sklearn.preprocessing.LabelEncoder: To convert fabric structure names to numbers for classification

2.6 Loading and image processing

This feature loads and converts images into consistently sized, black-and-white (128×128 pixel) images. The term "image preprocessing function" is frequently used to describe this function.

2.7 Loading data:

In this step, the CSV file containing the image data and its labels is selected

2.8 Read CSV file and process data:

Data from a CSV file (It is an abbreviation for Comma-Separated Values, and is used to store data in the form of a table (rows and columns) in text format, where the values are separated by a comma (,) or sometimes by other characters such as ;) is loaded in this step, and picture paths are extracted from the "Image Path" column and transformed into matrices that can be fed into the neural network.

2.9 Labels:

This stage extracts the numbers number of warp and weft threads per centimeter, which are the anticipated values and to fit the classification model and converts fabric names to integers and subsequently to a matrix representation.

2.10 Splitting data into training and testing:

This stage separates the data into %20 test 80% and training sets.

2.11 CNN model Structure:

Convolutional neural networks (CNNs) are built for image processing and to recognize different types of fabric weave structure and the number of warp and weft threads. They must be able to distinguish fine details, patterns, edges, shapes, and repetitions in an image. CNN structures automatically learn high-level descriptive features and details. A typical CNN is composed of several building blocks, such as convolutional, pooling, and fully linked layers. (13,14)

Because convolution and pooling methods allow CNNs to learn from a large number of images without requiring a large number of parameters, they are more efficient than traditional dense networks. CNN facilitates learning collaboration and the creation of a multi-output model.

A simplified flowchart illustrating the operation of CNN layers in this study is shown in figure 4.

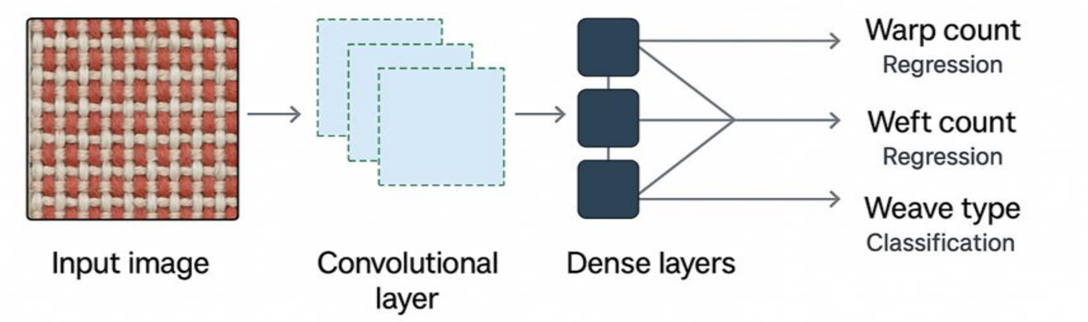


Figure (4) Layers of CNN model

As figure 4 shown: the proposed architecture consists of multiple layers designed to process fabric images efficiently. The input layer receives grayscale images of the fabric, each with a single color channel and resized to 128 × 128 pixels. These images then pass through convolutional layers, which progressively reduce dimensions while preserving essential spatial features such as fabric density, thread shape, and orientation. The convolution layer consists of two layers, the first of which is: a MaxPooling2D layer further downsamples the data by extracting the maximum value from small sliding windows, thereby reducing height and width dimensions while retaining the most critical attributes. The pooled features are then flattened into a 1D vector to prepare them for dense layer processing, with normalization ensuring optimal data scaling by the second flatten layer. Finally, fully connected (dense) layers analyze the extracted features, identifying complex patterns and relationships to generate the final prediction. This structured pipeline ensures a balance between dimensionality reduction and feature retention, enabling accurate fabric analysis.

2.11.1 Create three output tasks (Output Layers)

Here, the model addresses fabric structure and warp and weft data. Here, there are three output levels, each of which is in charge of a distinct task.

2.11.2 Model training:

Three outputs are predicted in this step when the model (model.fit) is trained using multi-output learning on the training data (X_train). The number of epochs for both training and tests is 20 training epochs.

2.12 Metrics used to evaluate a CNN model:

The following metrics were used to evaluate this multi-task model's performance, which combines regression and classification; each is described below.

2.12.1 Fabric classification scales:

2.12.1.1 Accuracy:

This metric indicates the degree to which the model can accurately forecast results.Here, accuracy refers to the proportion of photos that the model correctly identified based on the type of fabric weave structure.

As shown in the following equation, accuracy is a metric used to assess a classification model's performance. It is defined as the ratio of the number of correct predictions to the total number of samples.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

2.12.1.2 Categorical Cross-Entropy (Classification Loss)

It is a metric that computes the discrepancy between the actual class distribution and the expected probability distribution. The more accurate the model, the smaller the value. The most popular loss for Multi-Class Classification tasks, Categorical Cross-Entropy loss, is used in the fabric weave structure classification job of the built model.

2.12.1.3 Regression (Metrics used to measure thread count prediction performance):

Since this is a regression challenge rather than a classification one, the model does not use accuracy to gauge how well it predicts the number of warp and weft threads. Other metrics appropriate for regression are employed in place of accuracy, specifically (Mean Absolute Error (MAE)). MAE is a statistical measure used to evaluate the accuracy of a model in regression problems, as it measures the average size of errors between the predicted values and the actual values, without regard to the direction (whether the predictions are higher or lower than reality).

3- Results and Discussion:

In this experimental study, convolutional Neural Networks (CNN) (deep learning model) used to recognize different types of fabric weave structure and density of warp and weft threads. The performance of models such as accuracy, classification loss for fabric classification and mean absolute error for warp and weft densities were represented graphically and discussed.

3.1. Fabric classification scales

3.1.1 Accuracy

The accuracy of the results in the model training phase is 89.11% means that the model correctly classifies the fabric structure 89.11% of the time on the test data.

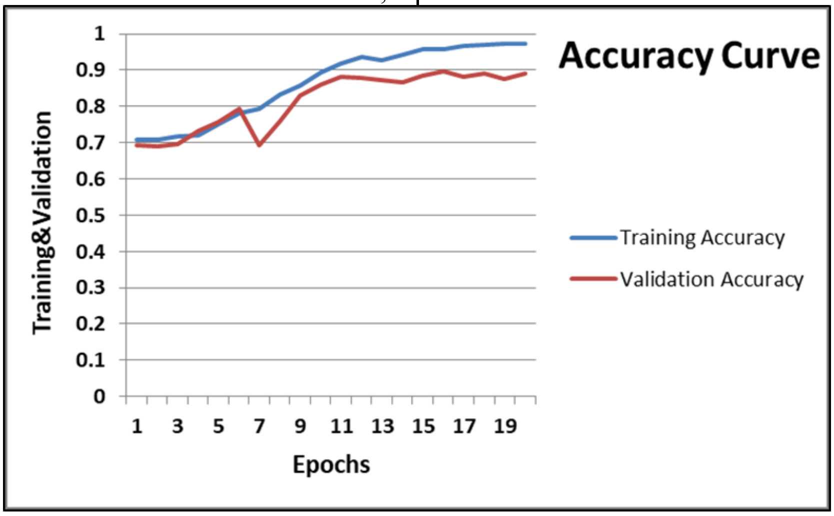


Figure (5) accuracy curve to evaluate a CNN model

As figure 5: the number of epochs (from 1 to 20) is represented by the X-axis. How many times the information has been processed across the whole form.

- Accuracy is represented by the Y-axis, with values ranging from 0 to 1, where 1 denotes 100% accuracy.

-The two curves' proximity to one another suggests balanced performance, avoiding overfitting and The training and validation accuracies were both near 0.75 at the beginning (from Epoch 1 to about 5). After thereafter, there was a discernible increase in accuracy between Epochs 6 and 10. Starting with Epoch 10, the training accuracy increased steadily, and by Epoch 20, it was close to 1 (100%) as well. With a few slight variations, the validation accuracy essentially stabilized at 0.85 and 0.89.

-According to experimental results, the CNN model's accuracy was 89.1% when evaluated with 100 images. It can identify around 89 photos properly, while it can identify about 11 photos inaccurately. This accuracy is considered excellent for data used to train the model; however we need better accuracy in the textile manufacturing industry.

3.1.1.2 Categorical Cross-Entropy (Classification Loss)

- In this model**:** structure output loss= 1.046

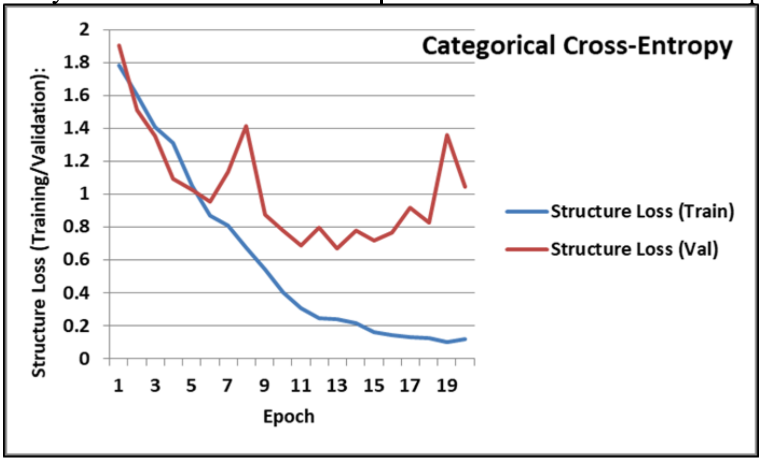


Figure (6)Structure Loss Curve – Train and Val for CNN model

As figure 6: the training and validation losses both decline from roughly Epoch 1 to Epoch 7, which is positive because it indicates that the model is learning effectively overall. Following Epoch 7, the red line (Validation Loss) starts to grow relatively high and becomes unstable. However, the training loss (blue) line keeps dropping sharply. This suggests that at roughly Epoch 7, the model started to overfit.

Given that there are 16 categories in this case, a value of 1.046 on the Categorical Cross-Entropy Loss scale (as displayed in the chart under Structure Loss (Val)) is comparatively acceptable. Although the model is less accurate on validation data, it performs well on training data.

3.1.2 Regression (Metrics used to measure thread count prediction performance):

3.1.2.1 Mean Absolute Error (MAE):

It measures the average absolute difference between the actual and projected values Its value is in this model**:**

-Warp threads: MAE ≈ 4.41± (on test data). This indicates that the model predicts the number of warp threads with an average inaccuracy of 4.41± threads/cm.

-Weft threads: MAE ≈ 3.25± (on test data). This indicates that the model predicts the amount of weft threads with an average inaccuracy of 3.25± threads/cm.

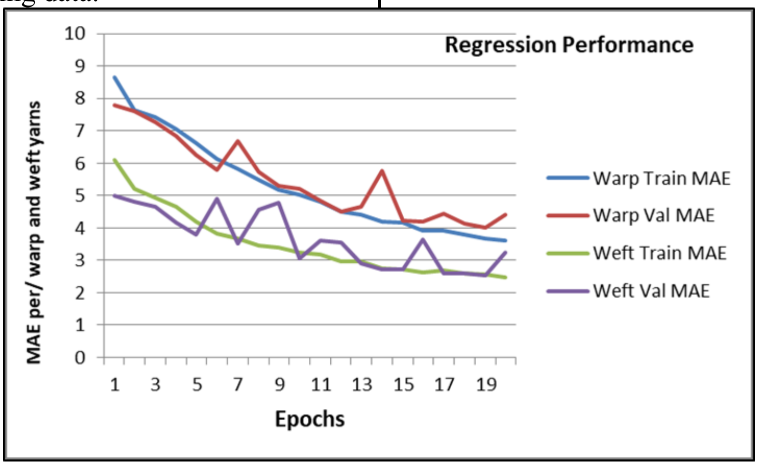


Figure (7) MAE Progress for Warp and Weft Predictions for CNN model

As figure 7:the graph shows that the model improves over time and its prediction error decreases. In both training and validation, the warp error is greater than the weft error, which could indicate that the model finds it slightly harder to predict warp density than weft density. Although we occasionally see high spikes in the validation MAE (especially the Warp Val MAE), the difference is negligible, suggesting that the model is not substantially overfitted. *Although the improvement is apparent, more regularization techniques or an increase in the number of epochs may be required to improve the stability of validation performance.

4-Conclusion:

In this work, we provide a deep learning model for identifying and categorizing woven textiles and calculating the quantity of warp and weft threads per centimeter. Convolutional Neural Network (CNN) model construction is the foundation of the suggested deep learning model. After preprocessing and image acquisition, data augmentation techniques are used to expand the dataset. CNN model used to extract high-level fabric features. The model was trained on the aforementioned woven fabric structures and counted the warp and weft threads in a single weave. The performance evaluated of our model using various performance metrics, such as accuracy**,** classification loss for fabric classification and mean absolute error for warp and weft densities**.** Experimental results showed that when tested with 100 images, the CNN model's accuracy was 89.1%. About 89 photographs are correctly recognized by it, whereas about 11 images are incorrectly recognized. For the quantity of data used to train the model, this accuracy is regarded as excellent; but, in the textile manufacturing industry, we require an accuracy that is better and regression (Metrics used to measure thread count prediction performance) Warp threads: MAE ≈ 4.41± , Weft threads: MAE ≈ 3.25± in academic research or a prototype is acceptable and shows that the model actually learns the relationships but is not accurate enough, as an error of ±4 threads/cm may cause fabric shipment rejection or specification issues. The suggested model has potential for the textile and fashion industries because it is computationally efficient and requires fewer parameters during training. We plan to expand our work to include additional woven and knitting fabric types in the future.

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