Textile Industries Wool Type Classification and Quality Identification Using Ensemble CNN and SVM

Sujanthi S
Assistant Professor
Computer Science and Engineering
M.Kumarasamy College of Engineering
sujanthis.cse@mkce.ac.in

Kavinkumar V N
Computer Science and Engineering
M.Kumarasamy College of Engineering
Karur,India
kavinkumar2k15@gmail.com

Gowthaman N
Computer Science and Engineering
M.Kumarasamy College of Engineering
Karur, India
gowthamann2212@gmail.com

Dhanush J
Computer Science and Engineering
M.Kumarasamy College of Engineering
Karur, India
dhanush.jd52003@gmail.com

***Abstract*— Chemical testing and microscopic examinations are often used to identify wool. Wool identification in the textile business needs a method of efficient detection so that different varieties of wool may be properly categorized. Human eyes are used in the conventional textile Wool identification detection technique, which is both inefficient and costly. We are utilizing an ensemble of convolutional neural networks to increase the precision with which we can classify wool used in textiles. Our suggested study makes contributions to the field of wool prediction in the textile industry by proposing the usage of ensemble CNN for the identification of wool. These methods include quality prediction, feature extraction, and picture processing. Better feature extraction, Wool stem/core segmentation, feature matching, and identification are all possible because to image processing. RCB-Gray conversion, Noise reduction, and Contrast enhancement are the three main kinds of techniques used in image processing. Wool and hairiness features may be retrieved using feature extraction and classification; features were extracted using an ensemble CNN trained with a custom parameter set. Wool is classified into the high, low, and medium categories based on the quality forecast. Experimentation on the suggested models may now be evaluated with respect to error rate, processing time, prediction accuracy, and prediction, recall and F-measure.**

Keywords*— *Wool parameters classification, CNN, SVM, feature extraction, and quality prediction

I. INTRODUCTION

Wool for textiles is a long, fine fiber that may be knit, woven, or intertwined in various ways to make a fabric. It can be a continuous filament or a twisted staple fiber. Fabrics are often crafted from wools formed by twisting or laying strands next to one another. It's up in the air whether the fibers are natural, synthetic, or a hybrid of the two. Today, there is a wide array of wools from which to choose, making possible textiles with a wide range of aesthetic and functional possibilities.

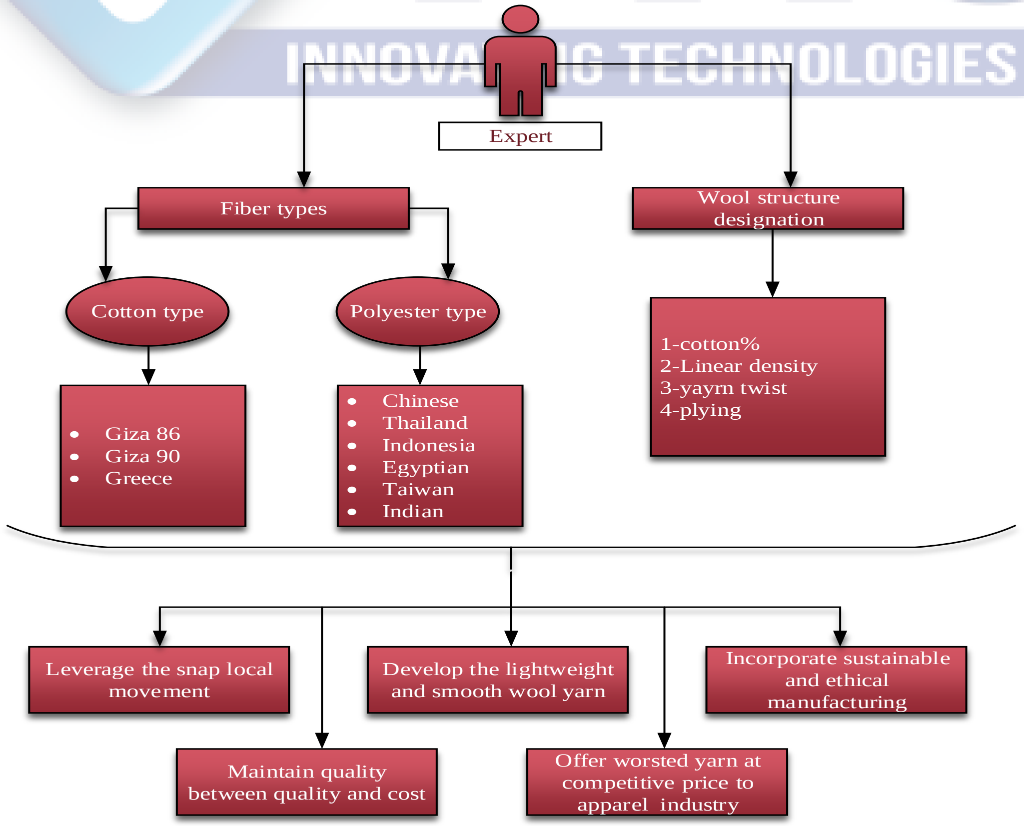

Figure 1. Experimental factor and wool market: Knitting a brighter future

In reality, there is a wide variety of ways in which wool may be defined, all of which rely on factors such as the kind of fabric, how it is constructed, the end-product efficiency, and the intended yarn performances during weaving or knitting. Physical or mechanical criteria including strength, elongation, toughness, as well as flexibility are used to characterize yarn bulk integrity, whereas yarn hairiness, resistance to abrasion, friction, as well as roughness are used to define yarn surface integrity. Further procedures like as hydrophilic finishing, dielectric finishing, flame-retardant finishing, resin therapy, and enzymes treatment might be used to classify yarn varieties when discussing technological fibrous products. Due to the wide range and intricate geometries of fabric flaws, detecting them is a difficult job in the fabric business. There have been several suggested solutions to this issue, but so far they have all suffered from slow detection speeds and poor accuracy. Classifying fabric flaws is a difficult but necessary step in ensuring high-quality fabric manufacture. Many potential deep neural network-based approaches have been presented in recent years. However, collecting enough fault photos to fulfill high-quality training would be tedious and time-consuming since defects are too infrequent in manufacturing. There are numerous important contexts in which fabric image retrieval might be useful, including textile product creation, e-commerce, as well as inventory management. However, it is difficult due to the wide variety of fabric styles.

Quality evaluation in the textile industry has used computer vision and machine learning to become more objective and cost-effective. Producing and selling high-quality wool requires precise estimates of many different characteristics. Snarling is a common problem in the wool manufacturing process, such as winding, warping, weaving, and knitting. Wool twists more than normal result in the formation of snarls. These defects can lead to wool breakage, damage to the fabric appearance, and color variation after dyeing. Using a high-quality wool-aramid blend wool as an example, this paper explains how the aramid fibers transform from loose ones to dominates and blend using wool tops during production, as well as the other crucial points of formation as well as quality control on each important working procedure as well as notes in the actual manufacturing procedure. The development of wool/aramid blended unique wools provides a prerequisite for the growth of advanced technology and superior quality safeguarding fabrics for the worsted wool products, as the wool test index varies depending on the special fiber mixture and the intended purpose or performance of the fabric or garment.

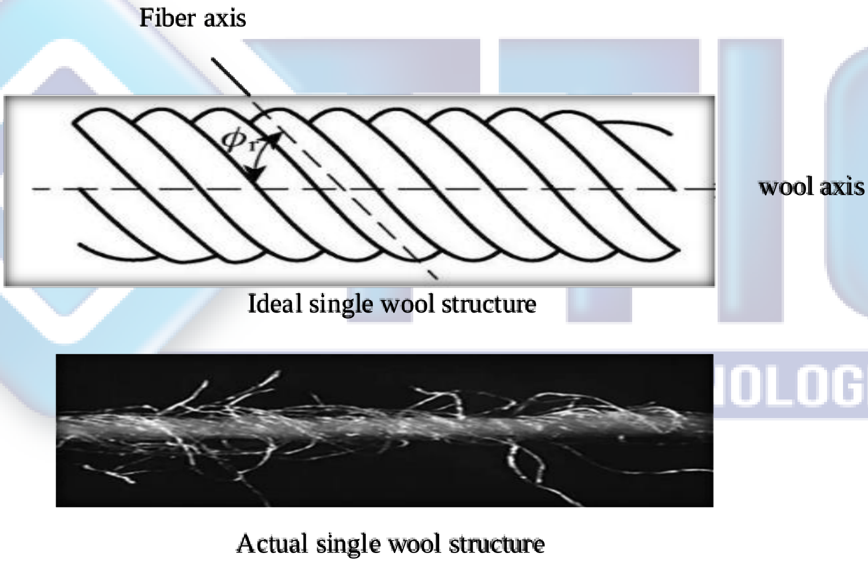

Figure 2. Actual and Ideal single wool structure

II. Related Work

[5] Inspired by the achievements of advanced convolutional neural networks (CNN), a deep learning framework has been applied to the problem of fabric image retrieving. The proposed method rests on the notion that, given a copy of the information in the labels, a deep convolutional neural network (CNN) may acquire a binary code and feature for representing the image. The suggested system employs an ordered search methodology that allows for both coarse- and fine-grained retrieving. In any case, the suggested framework is verified by the construction of a massive wool fabric image extraction dataset (called WFID) including over 20,000 pictures. This dataset is used for the longitudinal comparison trials necessary for self-parameter optimization, as well as the horizontal comparison tests necessary to prove the algorithm's superiority. The experimental findings show that the suggested framework is better to the competing one.

[6] YOLOv4 has advanced quickly as a traditional deep learning approach and end-to-end target identification algorithm, and it has been applied to many other fields with positive results. In this research, we propose a novel SPP structure that employs SoftPool rather than MaxPool to increase the accuracy of the YOLOv4 algorithm for detecting flaws in textiles. With three SoftPools, the enhanced YOLOv4 algorithm processes the feature map more efficiently, which helps mitigate the SPP structure's drawbacks and boosts detection precision. To ensure that the three The foundation produces are capable of being successfully provided into the one that follows PANet, the network's layout is improved through the inclusion of a series of layers of convolution that adhere to the SPP framework to decrease the channel's data of the feature map to an appropriate value. Furthermore, by implementing

contrast-limited histogram equalization with adaptive algorithms in advance, the image quality is enhanced, leading to potent anti-interference abilities as well as increasing the mAP. Experiments demonstrate that the improved YOLOv4 increases the mAP by a significant 6% in comparison to the initial YOLOV4, while only lowering the FPS by 2%. The enhanced YOLOv4 is not only useful in the defect detection industry, but may also be used in others.

To combat this problem [7], we offer a deep aggressive data enhancement technique called Defect Transfer. During network training, we do not completely connect the defect's location and size to the surrounding texture because the defect may occur anyplace on the background pattern and in any size. Using this premise as inspiration, we devise a cut-paste method to enhance the defect photographs by superimposing the faults on top of the original, imperfect pictures. Before the paste procedure, the flaws are randomly reshaped by scaling, rotation, and movement. We also present an adversarial transformation technique that modifies the copied faults to target the classification network's weaknesses, which should speed up the training process. Due to the wide variety of synthetic defect pictures used by the adversary, the network is pushed to acquire increasingly nuanced category characteristics. We demonstrate experimentally that with just 1% of fabric defect information on the ZJU-Leaper dataset, our technique achieves equivalent performance to current fabric defect classification algorithms. Even without human-annotated masks, Defect Transfer provides a significant improvement over conventional techniques of enhancement.

[8] The feature fusion modules in the structure brings together the advantages of both of the handmade characteristics as well as the CNN features. The methodology uses a pre-trained convolutional neural network and a multi-scale spatial masking method to extract both human-made and CNN features from images of woven fabrics. In addition, the framework includes a module for filtering out mislabeled data, which mitigates their effect during training. The suggested framework averages an assessment accuracy of 85.2%, 96.1%, as well as 100% in the trials, depending on whether the mistake is 0 degrees, 0.5 degrees, or 1 degree. In order to increase assessment accuracy and label noise resilience, feature fusion as well as mislabeled sample filtering were tested and found to be successful. When compared to current industry standards, the suggested approach for evaluating fabric smoothness performs quite well. This article has the potential to spark new lines of inquiry into the area of image-based fabric smoothness evaluation and related topics.

[9] This study suggests that quality features of cotton/elastane cores wool may be predicted using ANN (artificial neural network) and support vector machines (SVM) techniques. The predictive power of a model might suffer if given too many variables to work with, however techniques like principal component evaluation, and analysis of variances can help reduce the number of variables included in the equation. Data collected from a textile manufacturing facility is used to train and validate the prediction models. All of the algorithms are compared in terms of their performance on the test data. The accuracy of the models' predictions is measured using the mean absolute error in percentages, the mean absolute error (MAE), and correlation coefficient (R). Both the SVM and ANN models perform well in predicting most of the wool's quality parameters, with the SVM models doing somewhat better on many of the tests. The top models have been shown to have a MAPE and R success rate of above 90%. Specific quality features of the cotton/elastane base wool may be predicted with 91%, 93%, and 95% accuracy in terms of the Coefficient of Variation of mass (CVm) across the wool, hairiness, and Reisskilometer.

[10] The purity as well as tenacity of the raw wool fibers are significant factors in establishing the general caliber of the wool as well as the finished products made from it. The fineness of wool is a factor that is considered while sorting and selecting the fiber for various purposes. Eleven distinct sheep breeds had their fleece examined for fine as well as tensile attributes when the sheep were six years old and had their teeth clipped. Indigenous Menz, Wollo, Farta, as well as Tikur; exotic Awasi, Dorper, as well as Corrediale; and hybrids such as the 50% Awasi, 50% Dorper, 75% Awsi, and Washera/Awsi are all included. Wool fiber specimens were processed at 20 1 °C (68 2 °F) as well as 65% 2% RH (21 2% F) for 24 hours. The ASTM D2130-01 standard was used to choose the sample to take. The findings showed that there was a large variation in the fineness as well as strength of entire fibers collected from various sections of the sample sheep both within and across breeds. Ethiopian sheep wool wool was found to be acceptable for a wide variety of classical and technological uses, and a favorable association was found between fiber strength and fiber fineness.

TABLE 1: SURVEY PAPERS WITH MERITS AND DEMERITS

TECHNIQUES	MERITS	DEMERITS
Deep Convolutional Neural Network [5]	Retrieve levels, from coarse to fine, in a sequential searching approach	• Image quality assessment and preprocessing steps are essential in improving the wool quality prediction

classic deep learning method and end-to-end target detection algorithm [6]	The map of features may be efficiently processed using the enhanced YOLOv4 algorithms using three SoftPools.	• Within comparison to Greater R_CNN, it has lower recall as well as increased localisation error. • Due to the limitation of each grid's ability to suggest just two bounding boxes, detection of nearby objects is difficult. • Difficulty noticing details.
Scarce Defect Data [7]	A better discriminative network is required due to the wide variety of adverse synthesized defect pictures.	• The challenge in reported on DefectTransfer might result from ambiguous explanations, insufficient detail, excessively complicated tools that demand data the user may not have, as well as so forth. • The time it takes to create a bug report might exceed the time it takes to actually repair the problem. • There will be many flaws in a defect report that won't ever be corrected since the return on investment (ROI) isn't high enough if each low-priority fault is recorded.
feature fusion module [8]	Combining features as well as incorrectly identified sample filtering were tried and proved to be effective methods to improve assessor accuracy as well as label noise resistance.	• Feature fusion requires an innovative matcher to be designed and an important amount of practice examples to be acquired. • Wool quality predictions may be enhanced by assessing and preprocessing images.
ANN (artificial neural network) along with support vector machines (SVM) algorithms [9]	Most wool characteristics can be accurately predicted by either of the SVM as well as the ANN models	• In order to compute the wool quality, hairiness is one of the important parameter, which must be measured to predict the wool quality. • Furthermore, presence of noise degrades and affects the wool prediction accuracy.
Wool's fineness feature [10]	Fiber fineness was correlated positively with both fiber strength as well as fiber strength variance.	• Building, training, as well as distributing neural network algorithms at any scale is simplified with AWS.

III. Proposed Work

A. Research Gaps

Core wool is a kind of wool that consists of a filament fiber wrapped around another fiber. The textile industry is placing a greater emphasis on this sort of wool. Predicting the quality features of essential wool prior to manufacture is critical for avoiding erroneous fabric production. Thus, it is crucial for the textile business to create forecasting models. Employing fiber quality with spinning parameters, the evaluation of fabric smoothness look remains a difficult problem in the clothing and textiles business. Existing works use computer vision technology to characterize the look of fabric smoothness using a combination of hand-crafted picture features along with deep convolutional neural network, or CNN, based image characteristics. In this study, we provide a framework for the categorization of images that may be used to quantify the apparent smoothness of a fabric.

B. Proposed Methodology

The Contributions of our proposed are follows: (1) Image Preprocessing - Purpose of Image Preprocessing: It avoids irrelevant information and noisy information and only keep the valuable information of Wool and improve the quality prediction and simplify the data when predicts the image quality and thereby we can improve the feature extraction reliability, Wool stem/core segmentation, feature matching and recognition. There are three processes are considered as follows:

- RGB-Gray Conversion
- Noise Removal: For noise removal we proposed Improved Wiener Filtering, where we compute the SSIM (Structural Similarity Index) for true image and estimated image instead of minimizing Mean Squared Error (MSE).
- Contrast Enhancement: For image contrast level enhancement, we proposed Automatic CLAHE method, which is an extended version of CLAHE (Contrast-Limited Adaptive Histogram Equalization) algorithm.

(2). Feature Extraction & Classification - we extract features from Wool and hairiness extracted. For feature extraction we have used Ensemble CNN and set of parameters are considered as features that are categorized in following:

(1). Wool Unevenness (Negative Effect Parameters)
  → Irregularity
  → Imperfection
  → Hairiness

(2). Wool Strength (Positive Effect Parameters)
  → Tenacity
  → Elongation
  → Count Strength
  → Twist Factor
  → Wool Liveliness

(3). Wool Mass Parameters
  → Linear Mass
  → Diameter

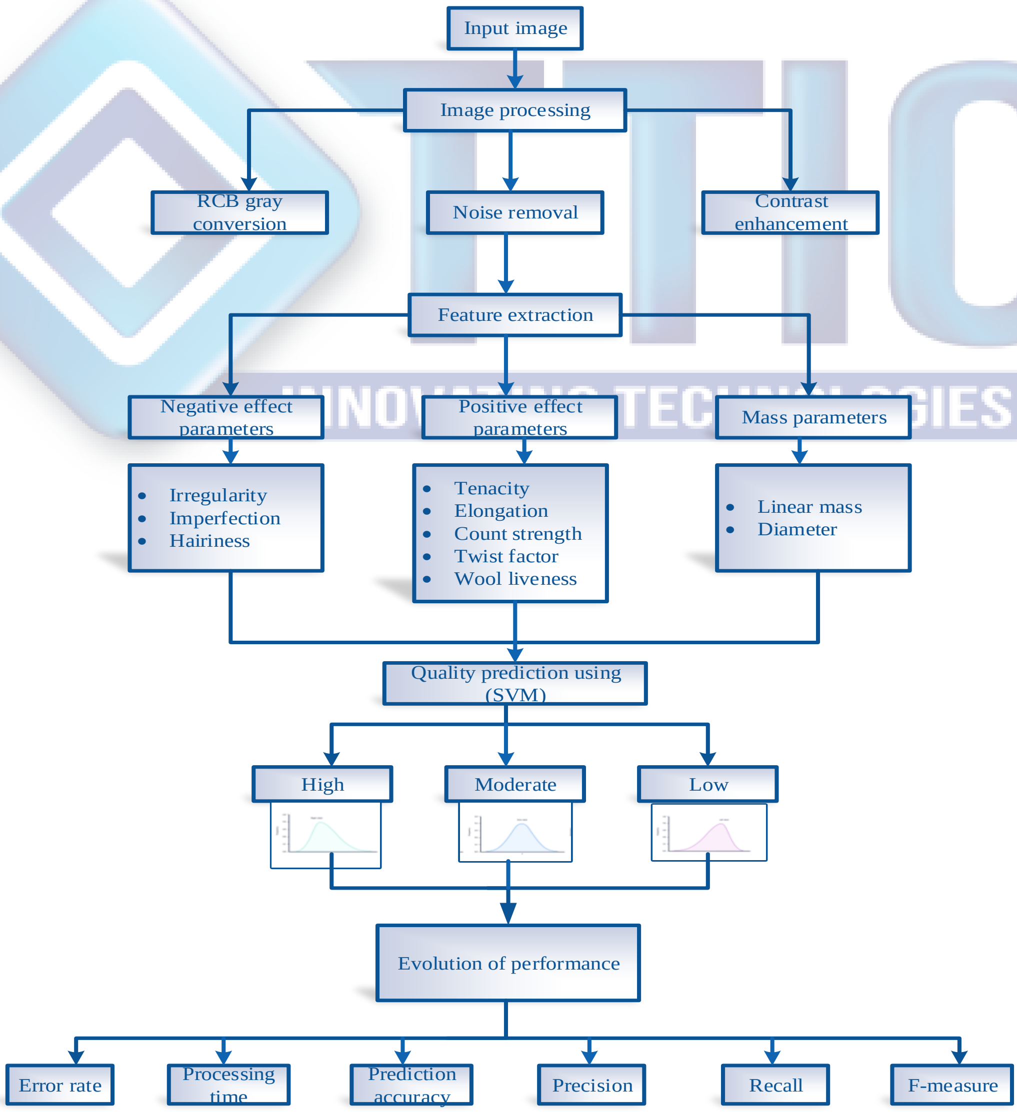

Figure 3: Block diagram

(3). Quality Prediction - SVM is used for Classification of clustered features. For classification we divided images into three classes: Low, High and moderate. The classification is primarily based on Wool features and other feature vectors.

(i). High
(ii). Moderate
(iii). Low

Finally, we perform the experimentation for evaluation the performance of the proposed model by following: Error Rate, Processing Time (s), Prediction Accuracy (%), and ROC Curve

IV. RESULTS & DISCUSSION

A. Implementation Details

The recommended approach is implemented in the Python IDLE 3.8 environment. Software and hardware configuration possibilities for the installation are shown in Table I.

TABLE 2
ENVIRONMENT SETTINGS

Hardware Settings	Processor		3.00GHz
	CPU		Dual Core
	RAM		4 GB
	Hard Disk		1 TB
Software Settings	OS		Windows 10 (64bit)
	Python IDLE		3.8
	Library used		
	a)	imutil	0.5 .3
	b)	argparse	1.4 .0
	c)	numpy	1.19 .2
	d)	dlib	19.21 .0
	e)	cmake	3.18 .2 .postl
	f)	pip	20.2 .3
	g)	opencv-python	4.4 .0 .44
	h)	wheel	0.35 .1
	i)	pillow	7.20
	j)	matplotlib	3.3 .2 -cp38
	k)	scipy	1.5 .2 -cp38
	l)	tensorflow	2.3 .1 -cp38
	m)	keras	2.4 .3
	n)	pygad	2.8 .1
	o)	resource	0.2 .1
	p)	sklearn	0.0
	q)	scikit-image	0.17 .2
	r)	elm	0.1 .3
	s)	nano-python	2.0 .1
	t)	yolo-v4	0.5
	u)	image-slicer	2.1 .1
	Command used	Pip	
			package name

B. Experimental Results

The proposed method is put through its paces using current information from the Wool dataset. Training, testing, as well as validation data are collected and archived separately. The information set was split in half, with 20% utilized for training and 80% placed through validation and testing. Several efficiency criteria, including Precision, Recall, as well as F measure, are utilized to evaluate wool quality prediction algorithms. The effectiveness of the suggested strategy was evaluated against that of CNN methods. Overall, testing shows that Ensemble CNN is more accurate than CNN.

Multiple steps are taken to analyze the images of the wool to assess the caliber of the wool utilizing deep learning. Precision, Recall, F-measure, Error Rate, as well as Accuracy were calculated using true positive, false positive, false negative and real negative values on the feature instance generated by feature vector clustering to evaluate performance. The resultant vector of features is divided into classes, and each class is analyzed separately.

Table 1 summarizes the results of the forecasting system. Wool hairiness identification, in particular, is simplified because to the variety of wool qualities and the results roughly reflect the wool's quality.

Table 3: Performance Evaluation of Autonomous Segmentation Techniques

Class	Technique	Precision	Recall	F measure	Error Rate	Processing Time	Accuracy
Cotton	Proposed model	0.9978	0.9412	0.9989	0.2	16ms	99.5
	CNN Existing Model	0.9890	0.9340	0.9850	0.5	34ms	92
Polyester	Proposed model	0.9965	0.9514	0.9971	0.2.5	15ms	98
	CNN Existing Model	0.9840	0.9420	0.9895	0.4.5	36ms	90
Silky	Proposed model	0.9956	0.9615	0.9965	0.3	14ms	95
	CNN Existing Model	0.9820	0.9398	0.9850	0.4	35ms	91

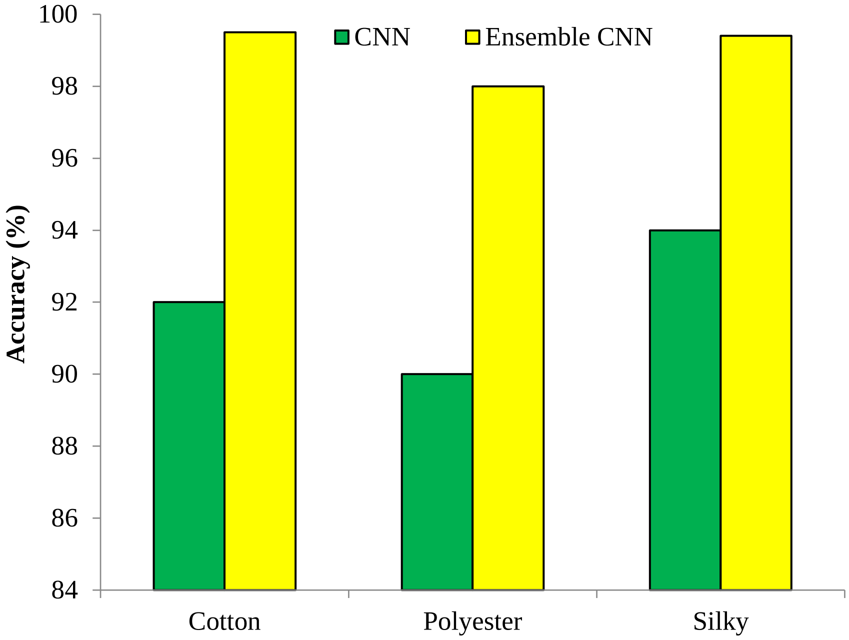

Figure 4. Accuracy Performance for Different Wool Types

The preliminary information collected allow for confident assumptions on wool quality. It produces more reliable positive values in the feature set calculation. The Ensemble CNN provides the most useful comparisons for evaluating wool. Table 1 displays the outstanding outcomes obtained from a recall's value,

The suggested model's excellent accuracy ratings in forecasting wool quality are notable. Finally, when compared to other machine learning methods, the model suggested obtains an accuracy of about 99% on the f measure. For the textile business, the suggested framework based on the architecture of deep learning may be utilized to assess wool.

V. Conclusion

In most cases, chemical and microscopic tests are used to identify wool. The textile industry needs a means to efficiently recognize the several forms of wool identification. Human eyes are the conventional way for identifying wool in textiles; nevertheless, it is exceedingly inefficient and expensive. We are employing ensemble CNN to increase the classification accuracy of the wool categorization in textiles. We employed three ways in our Ensemble CNN mechanism to identify the kind of wool, which is one of the contributions of our suggested study for wool prediction in the textile industry. They are quality prediction, feature extraction, and image processing. Image processing may increase the accuracy and reliability of feature extraction, Wool stem/core segmentation, feature matching, and feature identification. There are three different categories of image processing operations: RCB-Gray conversion, Noise reduction, and Contrast improvement. Wool and hairiness may both have their features retrieved via feature extraction and classification. To extract the wool's features, ensemble CNN was used along with a set of parameters. The wool is classified into three quality categories, High, Low, and Moderate, according to the quality forecast. In order to test the provided models, we may finally assess the error rate, processing time, prediction accuracy, and prediction, recall and F-measure.

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