Intelligent cotton ball maturity prediction model for smart agriculture

Pooja Verma; Gagandeep Kaur; Rajendra Machavaram; Mahua Bhattacharya

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Intelligent Cotton Ball Maturity Prediction Model for Smart Agriculture

Pooja Verma¹,a), Gagandeep Kaur ²,b), Rajendra Machavaram ¹,c) and Mahua Bhattacharya ³,d)

¹ Indian Institute of Technology Kharagpur, West Bengal, India
² Bennett University, Greater Noida, Uttar Pradesh, India
³ ABV- Indian Institute of Information Technology & Management, Gwalior, Madhya Pradesh, India

a) pooja.verma899@gmail.com
b) Corresponding author: gagan873@gmail.com
c) rajendra@iitkgp.ac.in
d) mb@iitism.ac.in

Abstract. The agricultural industry is the most prominent sector for the economic growth of the country. Cotton is an important crop that brings out major returns to the economy. In the current era, smart agriculture technology is incorporated which includes various modern techniques such as sensors, artificial intelligence, and computer vision to digitalize the whole process. This digitalization through modern technology enhances the fast and intelligent productivity of crops. In this paper convolutional neural network-based methods have been used to predict the maturity of the cotton balls using image features of mature and immature images. Real-time maturity detection is a challenging task for cotton fiber because of the many constraints in natural light conditions and environmental effects. The proposed scheme uses annotation to classify the cotton balls. The classification is labeled as mature and immature images then the annotated images are used for training the deep learning models Resnet 50 and VGG 16. The average accuracy achieved from these methods is 92.47% for Resnet 50 and 96.58% for VGG16. The loss of the model is 21.05% for Resnet50 and 14.91% for VGG16.

INTRODUCTION

The textile industry plays a key role in the global economy. As the population increases, textile product demand will continue to increase. Thus, to increase the textile products more concentration is required on cotton fiber production. Traditional agricultural methods in cotton fiber production must be complemented by new innovative and advanced technologies [1]. This will accelerate cotton productivity to a more advanced level. Cotton is one of the most significant crops in industrial raw material which produces several textile products. Cotton is popularly known as a “Cash crop” or “White Gold”. The high quality and high productivity of cotton depend on the raw material. The raw materials should produce more accurate fiber quality. Precise cotton fiber quality measurement systems are required to observe several variables, of which maturity of the cotton is the most important [2, 3]. More mature cotton fibers are required because they produce superior quality yarns and fabrics, and they have better dye affinity. It is a significant characteristic of cotton fibers. Thus, the motivation of the proposed scheme is to improve processing and removing excess waste obtained from short and immature fibers, the development of fiber maturity prediction technologies is of foremost importance for the cotton industry [4]. Cotton fiber maturity is defined by the degree of development of cotton fiber. The maturity of the cotton material tells us how much development has taken place in the fibers. This difference in the maturity of various fibers appears because of the variations in the degree of the secondary thickening or deposition of cellulose in fibers [5-7]. Cotton fiber maturity can be measured from the cotton’s secondary cell wall thickness. There are several existing techniques to measure cotton fiber maturity. However, there are several drawbacks to the existing approaches such as poor prediction accuracy, and precision. Besides these limitations, there are no direct measurement methods available for maturity that are fast and reliable. In this paper, a deep learning model is proposed that predicts the average maturity of
cotton fiber farmland so that farmers can get an idea about harvesting cotton. The agriculture industry plays a major role in the global economy. The sensors in the industrial internet of things helps to collect various physical parameters and camera helps to take image of agriculture field including crops such as cotton, etc [8]. The cotton industry consumes cotton as its principal raw material and contributes about 14% of the GDP to the world economy. It is required to produce more cotton raw materials to fulfill the demand. This is achieved by analyzing the cotton fiber characteristics in which maturity is the most important characteristic which is the motivation behind the proposed work. In the internet of things based agriculture environment deep learning technology is widely adopted for various applications [9]. Deep learning is an artificial intelligence technique that helps to make accurate predictions. In this paper, the major contribution is the prediction of the fiber maturity through novel deep learning models, which is fast, accurate, and precise that results in enhancement of cotton production significantly.

### Table 1: A comparative analysis of the existing system

<table>
<thead>
<tr>
<th>Authors, Year, Journal</th>
<th>Technique Used</th>
<th>Brief Summary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kljun et al. [1], 2014</td>
<td>Transmission Electron Microscopy (TEM), Interferometry, Attenuated Total Reflectance Fourier transform Infrared (ATR–FTIR) spectroscopy, Immune - fluorescence labeling, and fluorescence spectroscopy</td>
<td>This paper presents measurement of different states of cotton ball maturation and during the maturation stage of cotton fiber, secondary wall thickening, microware, Birefringence, water loss from lumen intermolecular hydrogen-bonds are observed.</td>
</tr>
<tr>
<td>Turner et al. [11], 2017</td>
<td>Histogram specification, Machine learning, Regression, Transfer learning</td>
<td>This paper uses new transfer learning approach with single feature commonly used by older instrument that transfer information related to fiber characteristics using different regression technique.</td>
</tr>
<tr>
<td>Yeom et al. [16], 2018.</td>
<td>Region growing algorithm, Otsu Thresholding, Random sampling, Morphological filtering</td>
<td>This paper purposes cotton ball detection and estimation method using UAV. Region growing and random sampling used for detection average accuracy achieved 88% with strong correlation factor 0.8.</td>
</tr>
<tr>
<td>Suna et al. [7], 2019.</td>
<td>Double thresholding with region growth algorithm, Linear Hough Transform, Linear regression model.</td>
<td>To efficiently count and predict the cotton ball these techniques are used. Average accuracy 83% achieved for 2D images and mean absolute error is 8.92% with different whether condition.</td>
</tr>
<tr>
<td>Sanjay et al. [6] 2021.</td>
<td>Image Processing, Machine learning</td>
<td>This paper discusses about different equipment and technique for cotton ball prediction as well as for harvesting that increases yield quantity by 20-25%. This paper presents measurement of different states of cotton ball maturation and during the maturation stage of cotton fiber, secondary wall thickening, microware, Birefringence, water loss from lumen intermolecular hydrogen-bonds are observed.</td>
</tr>
</tbody>
</table>
RELATED WORK

This section describes literature review of the state-of-the-art approaches for predicting cotton ball maturity. Adedoyin et al. [10] proposed a technique to measure the maturity of cotton balls. In this technique, cross-sectional image analysis and the perimeter of the fiber are used to measure the maturity of cotton balls. It is used as a reference method in many maturity measuring methods. Turner et al. [11] proposed polarized light microscopy (PLM) based technique for cotton maturity prediction. In this technique, polarized light is used to differentiate the cotton fiber using double refraction that divided light into two parts. When two light beams come out with different speeds and phases are passed by the analyzer. It moves both beams on the oscillation plane to find maturity based on the color produces by oscillation. The main drawback of this approach is poor performance due to human subjectivity and contains high variance of the measurement. Paudel et al. [12] proposed the Advance Fiber Information System (AFIS) which measures various parameters of cotton such as length, maturity, neps, and trash. In this approach, individual fibers length and maturity are measured by passing the light beam through the fiber and analyzing the electro-optical signal. However, the main limitation of this approach is due to the presence of fiber crimps length measurements of the cotton fiber being biased. Shahriar et al. [13] proposed a machine vision system to obtain longitudinal images of cotton fibers. In this approach, the average maturity of cotton is measured by using image and pattern analysis. Also, it measures maturity from the auxiliary training data generated by the cross-section of the longitudinal view of the image. Rodgers et al. [14] proposed cottonscope which is based on siromat technology to measure fiber maturity and fineness of weighted fiber cotton. Cottonscope is faster than siromat and uses PLM and other advanced technologies. In this approach, water is used instead of castor oil which improves sample preparation and makes the technique more user-friendly and quicker. There are various existing approaches available for maturity measurement, but they fail to achieve real-time monitoring or prediction of the maturity of cotton fiber. Also, they have low accuracy, time-consuming and costly [15-17]. In this paper, to address the issues and to increase the accuracy of the fiber maturity deep learning approach is proposed. The deep learning approach promises higher accuracy and precision results for large datasets [18-20]. Table I shows a comparative analysis of the existing system.

MATHEMATICAL MODEL

Cotton maturity can be mathematically modeled in two ways as cross-sectional method and Ford’s equation. The cross-sectional measurement of cotton fiber is the most accurate technique to determine the maturity of cotton fiber and is used as a reference method to calibrate other methods [6-9]. The maturity of cotton determined by the degree of thickening of cotton is called $\theta$ and it is the ratio of the cross-sectional area and perimeter of the cotton. $P$ is the fiber cross-sectional perimeter. The cross-section of cotton fiber is defined by the difference between the core fiber area and the total fiber area [1].

$$A_w = A_1 - A_2$$

$$\theta = \frac{4\pi A_w}{P^2}$$

Cotton fiber maturity ratio $M$ is calculated as:

$$M = \frac{\theta}{0.577}$$

PROPOSED SCHEME

In the proposed scheme, cotton ball maturity is predicted using deep learning models. Two different Convolutional Neural Network (CNN) methods VGG16 and Resnet 50 are used to predict the maturity of cotton fibers. VGG 16 consists of 16 layers with different weights. The network of the VGG16 model contains very large parameters that are about 138 million parameters. It contains many convolutional layers followed by pooling and activation layers with different number of strides. The architecture of this model follows the same arrangement of convolution and max pool layers consistently and at the end of the network, it contains a fully connected neural network and softmax activation function for the output. Residual Network 50 (Resnet 50) uses residual learning of the data, and it has 50 numbers of layers for its operation. Resnet model is learned by residual instead of features and it subtracts the features from the input layer. It directly connects the input of the nth layer to some of the (n+x)th layers.
In this paper, the image annotation tool MakeSense.ai is used to classify and label mature and immature image datasets. Make Sense.ai is an image annotation tool used for deep learning and AI applications. Image annotation is a process of labeling and classifying an image. It classifies features of the image datasets and is used in deep learning to learn to recognize different objects. In this paper, Kaggle open-source dataset is used [15]. The model architecture of the proposed scheme is shown in FIGURE 1. In this proposed architecture, firstly dataset is collected from Kaggle then it is rearranged and redefined for image annotation. By using image annotation classify the image into mature and immature labels and get the exact area of the cotton balls. These annotated images are used for training the deep learning models. In the proposed scheme, two different convolutional neural networks VGG16 and Resnet50 are used. Both deep learning models were trained with the same data sets to predict the maturity of the cotton balls. After training and validation of the dataset, the prediction is applied to new cotton ball images.

![FIGURE 1 Proposed Model Architecture](image)

**RESULTS**

This section analyses the performance of the proposed scheme. In the proposed scheme, the results are achieved using deep learning models such as Resnet 50 and VGG 16 in terms of average accuracy and loss.

**Resnet 50**

In this mechanism, to predict the maturity of cotton balls trained and validate the model using annotated images. For training and validation batch size =32 and target size (224, 224) are used. Adam optimizer used as an optimization technique and for the loss function categorical cross entropy used for this model. Here number of epochs =20 used for training and result of the training dataset. From FIGURE 2 and FIGURE 3 shows maximum validation accuracy of the model is 92.47% and minimum validation loss of the model is 21.05%. FIGURE 4 shows the maturity predicted images using Resnet 50 model.

![FIGURE 2 Accuracy Plot](image)

![FIGURE 3 Loss Plot](image)

**TABLE 2 Training dataset using Resnet50**

<table>
<thead>
<tr>
<th>Epoch</th>
<th>train_acc</th>
<th>val_acc</th>
<th>train_loss</th>
<th>val_loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>10/20</td>
<td>0.943</td>
<td>0.954</td>
<td>0.0320</td>
<td>0.0342</td>
</tr>
<tr>
<td>15/20</td>
<td>0.950</td>
<td>0.960</td>
<td>0.0280</td>
<td>0.0300</td>
</tr>
</tbody>
</table>

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VGG 16

In this mechanism, to predict the maturity of cotton balls using VGG 16 training and validation batch size = 32 and target size (224, 224) used. Adam optimizer used as an optimization technique with learning rate = 0.01 and for loss function categorical cross entropy used for this model. Here the number of epochs =10 is used for the training dataset and the result of the training. From the FIGURE5 and FIGURE6, shows maximum validation accuracy of the model has gone 96.58% and minimum validation loss of the model is 14.32%. FIGURE 7 shows the maturity prediction using VGG 16 model.

<table>
<thead>
<tr>
<th>TABLE 3 Training dataset using VGG16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epoch 9/10</td>
</tr>
<tr>
<td>16/16 [--------------------------------] - 1879s 50it/step - loss: 0.1341 - accuracy: 0.8088 - val_loss: 0.8321 - val_accuracy: 0.7397</td>
</tr>
<tr>
<td>Epoch 20/10</td>
</tr>
<tr>
<td>16/16 [--------------------------------] - 1877s 50it/step - loss: 0.2570 - accuracy: 0.9028 - val_loss: 0.9404 - val_accuracy: 0.8658</td>
</tr>
</tbody>
</table>

FIGURE 4 Maturity Predicted images using Resnet 50

FIGURE 5 Accuracy Plot

FIGURE 6 Loss Plot

FIGURE 7 Maturity prediction using VGG 16 model.
CONCLUSION

The deep learning technologies are widely applied in agriculture and provide accurate results for large areas of datasets. This paper proposes an intelligent cotton boll maturity prediction model using deep learning. The result provided in terms of accuracy by Convolutional neural network models Resnet 50 and VGG16 are improved as compared to other state-of-the-art algorithm which helps farmers to predict maturity in large farmland of cotton balls. It helps farmer take valuable decision such as decide maturity of cotton balls and take timely decision to harvest farmland. Furthermore, it also helps in health monitoring of the cotton crops. In the future work, we will consider different image acquisition conditions and geographical region for predicting cotton balls maturity.

REFERENCES