Convolutional Neural Network for Cotton Yield Estimation

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Abstract: The objective of this paper was to estimate the cotton yield potential of different cotton varieties using high-resolution field images based on a convolutional neural network (CNN). The yield estimation for different cotton varieties in grams in breeding studies has a great importance for the determination of superior cultivars to be commercialized. Due to the cost and excessive time consumption typical of traditional methods, alternative ways for cotton yield estimation have been investigated over the years. This paper proposes an automated system for cotton yield prediction based on color images obtained by an unmanned aerial vehicle (UAV). Two replicational field experiments including three different cotton genotypes were conducted at May Seed R&D station in Torbali, Izmir, Turkey. Three different planting patterns including three, four and six rows, respectively in ten-meter wide areas were used as experimental plots. The ground-truth yield values for a total of six hundred planted areas were obtained by weighing the harvested cotton bolls after field images were taken. Achieving an absolute difference of no more than 350 grams for 114 out of 120 planted areas which were randomly selected only for testing purposes indicates that the CNN can effectively capture important features related to cotton yield from the field images obtained by the UAV. The combination of drone technology with reliable CNN models holds great potential for optimizing agricultural practices, improving agricultural productivity, and reducing operational costs.

Keywords: Deep learning, Image processing, Convolutional neural networks, Backpropagation neural networks.

1. Introduction

Cotton (Gossypium hirsutum) as the world's leading fiber crop, plays a significant role in the agricultural economies of many countries (ITC, 2007; USDA, 2020). As global cotton consumption has been increasing notably in recent years, the development of superior cotton varieties that are adaptive to various environmental conditions, and have high yielding, and disease tolerance is the foremost task for cotton breeding programs. Such a challenging mission involves several years of field testing of different cotton genotypes before deciding whether any of them is worth releasing as a new variety for commercial production.

High yield is one of the most significant selection criteria along with fiber quality for attaining cotton varieties desired by farmers during plant breeding field experiments. Therefore, each genotype is investigated in terms of yield performance, and the data obtained from potential cotton varieties planted in smaller areas is used to predict the yield performance for large-scale farmer fields. Conventional methods for determining yields of cotton varieties in breeding studies are either machine harvest or handpicking of cotton bolls. While the former is economically challenging due to the cost of a cotton picker, the latter is more time-consuming and requires an excess workforce, and is prone to field accidents. These drawbacks therefore limit the number of new cross combinations to be tested in a season. This results in a lower chance of getting superior variety among chosen populations and may prolong the development of new elite lines.

This paper proposes an alternative, faster and cheaper effective method for cotton yield estimation, using UAV acquired images of several small experimental cotton culture areas, that are processed by a regressive CNN. In the last decade, advances in CNN architectures proved excellent capabilities in image processing and analysis for both classification and regression tasks (Belean, 2021). Classification tasks categorize input data into predefined classes, on the other hand, regression tasks predict a continuous numerical value based on input data such as predicting the cotton yield in units of grams based on UAV images. The preliminary experimental results are promising, although future extensive testing and improvements are still necessary.

The remainder of this paper is organized as follows. In Section 2 some relevant related works

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are briefly outlined. Section 3 describes the sowing patterns and analysis methods, CNN and Backpropagation Neural Network, in detail and provides actual field harvest data obtained for crop handpicking. Section 4 presents and discusses the results obtained by employing the CNN, which are compared with the actual field data to demonstrate the accuracy of the proposed method. Section 5 includes the conclusion of this paper and outlines possible future directions for improving the results obtained by the CNN by incorporating various trait data such as plant height, biomass, and normalized difference vegetation index (NDVI).

2. Related Work

Considering the limitations encountered for traditional methods, seed companies, as well as universities and institutes, have been in the search of alternative ways to accelerate the collection of field data for several years (Huang & Thomson, 2015). Satellite images have been initially used to estimate cotton yielding by calculating crop vegetation indices (VIs) (Alganci et al., 2014) and by leaf area index (Chen et al., 2015). However, predefined data collection times and cloud blockages reduce the efficiency of satellite images taken from the fields. Therefore, unmanned aerial vehicles (UAVs) have been widely preferred in recent years for data collection in high-precision agricultural studies to monitor crop development at various stages. The collected data was analysed by using different techniques such as the determination of vegetation indices (VIs) to estimate plant health and phenotypic traits (Chen, 2019; Xia et al., 2019; Xu et al., 2019) and predict yield potentials (Karahan et al., 2023).

In (Amin et al., 2023; Yeom et al., 2018), it was emphasized that images were taken by the unmanned aerial vehicle (UAV) in high spatial and temporal resolutions of agricultural lands to facilitate timely and accurate data collection. For this purpose, an automatic open cotton boll detection algorithm was proposed in the context of utilizing ultra-fine spatial resolution UAV images. To provide computational efficiency, seed points were hierarchically created on a random basis. Spectral threshold values that automatically separate cotton bolls from other non-target objects were obtained based on input images for adaptive application. As a result, a binary cotton boll classification was carried out using threshold values and other morphological filters. The open cotton boll classification results were validated using reference data, and the results showed that the accuracy was more than 88% for various evaluation measurements. Besides, this study utilized these target regions on UAV images for direct cotton yield prediction. In this paper, by contrast to the aforementioned study, the images were fed directly to the CNN without using any binary classification.

In (Nguyen et al., 2019), they claimed that an estimated model working on crops such as wheat, rice, and sugar cane would fail to predict cotton yield. They developed a new Spatial-Temporal Multitasking Learning algorithm to predict on-farm crop yields between 2001 and 2003 in West Texas. They have integrated multiple heterogeneous data sources with this algorithm. Thus, they combined the spatial-temporal properties by learning different properties simultaneously and adding a weighted regulator to their loss functions. The authors claimed that this was one of the first attempts to predict fine-grain cotton yield using the Multitasking Learning approach and deep learning for in-field cotton prediction.

Manoharan & Thangavelu (2018) built a novel integrated fuzzy approach for finding the influential factors as well as for the ranking of the factors related to the cotton yield based on a fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL). They utilized Fuzzy Cognitive Maps (FCM) and their important elements for the assessment of cotton yield prediction and proposed the interdependence of every factor on each other and specified how it directly or indirectly affected the cotton yield using hybrid DEMATEL and FCM. They claimed that their solution using FCM provided accurate prediction, that is 98% accuracy, for the small cotton yields obtained.

In (Papageorgiou et al., 2011), they also used a Fuzzy cognitive map (FCM) to estimate cotton production. The developed FCM model consists of nodes connected by oriented edges where the nodes represent the main factors affecting cotton crop production such as texture, organic matter, pH, elements such as K, P, Mg, N, Ca, Na and cotton yield. It was evaluated for 360 cases measured for a duration of six years (2001-2006) for a 5-hectare experimental cotton field. They concluded that the FCM technique performed better in most of the cases when compared with the benchmark machine learning approaches. They concluded that the proposed FCM simulation model can estimate cotton yield with reasonably high overall accuracy and it was sufficient for this specific application area.

Tedesco-Oliveira et al. (2020) found a solution based on deep learning to identify and count cotton bolls using commercial crop imagery in different computational scenarios and used this information to predict cotton yield. They developed an automated deep learning system to predict cotton yield working in less than a second, which is fast enough for real-time information. They declared that the best result was found for a scenario with an average computational demand and attained a mean percentage error of 8.84%. Furthermore, their solution featured a higher information generalization capability and robustness to environmental conditions. They claimed that based on these settings reliable yield predictions could be obtained at any time throughout the day.

3. Materials and Methods

The contributions of this study are stated below:

- A CNN neural network model was developed to estimate cotton yield in units of grams using UAV images;
- After the training of CNN, many UAV images were collected and the estimation of cotton yield in units of grams for these images was performed in less than 5 seconds;
- The proposed approach for predicting cotton yield performance is time and cost-effective. Instead of harvesting all genotypes planted in thousands of rows, only the varieties having superior performances predicted by CNN will be handpicked and sent for further fibre quality and yield analyses. This reduces labour cost drastically and enables the testing of more cross combinations within a season. With more crosses tested, the possibility of obtaining desired traits in the lines or variety will increase which may lead to a higher chance of getting leading varieties in a shorter time for the market.

For this purpose, two replication field experiments were carried out at MAY Seed Research and Development station in Torbali, İzmir, Turkey. Three different cotton varieties were planted in three different sowing patterns and high-resolution field images were taken before harvest and fed into CNN.

A sample of an UAV image utilizing a Mica Sense Red Edge camera is illustrated in Figure 1. In this cotton field, four different cotton genotypes (different seeds) were planted. All varieties concerned were accepted as early maturity cotton varieties and their fiber parameters were at acceptable levels for standard growers and yarn

Figure 1. Unmanned aircraft vehicle image of cotton fields at Torbali, Izmir, Turkey.

manufacturers. They were developed through the MAY seed cotton breeding program and shared no mutual paternal or maternal parent background at the beginning of crossing. Each cotton variety was planted in six rows. After these six rows reached germination, some rows were cut to create different trial patterns (Planting Patterns). The rows are 10-meter wide, and planting patterns which include either one planted row or one empty row or 2 planted rows and one empty row and so, are used.

In general, plants that can find enough open space around them tend to produce more cocoons. However, the commercially planted pattern is the one without any gaps.

The yield (ground-truth) data in Table 1 was obtained for each seed's two-row variety. Six hundred planted areas were prepared. Table 1 shows only 18 of them. The most homogeneous and productive rows were selected for further analysis by genetic engineers.

Two different machine learning methods were tested with UAV images for the six hundred planted areas. Images were taken towards the end of the growing season with the same drone that had a Mica Sense Red Edge camera mounted on it during early morning. Early morning was chosen because the sky was clear and there was minimal wind at that time. Timing was coincided with the period when bolls were nearing maturity but before they were harvested.

Table 1. The actual (ground-truth) cotton yields in grams for Figure 1

Genotype Code	Planting Pattern	Data Number	Data (Yield in grams)
1	No skip:1	1	2700
1	No skip:1	2	4800
1	2 in 1 Skip:2	3	6500
1	2 in 1 Skip:2	4	8100
1	1 in 1 Skip:3	5	7300
1	1 in 1 Skip:3	6	9200
2	No skip:1	7	5000
2	No skip:1	8	5700
2	2 in 1 Skip:2	9	7500
2	2 in 1 Skip:2	10	9400
2	1 in 1 Skip:3	11	7600
2	1 in 1 Skip:3	12	10200
3	No skip:1	13	5200
3	No skip:1	14	3700
3	2 in 1 Skip:2	15	6200
3	2 in 1 Skip:2	16	8700
3	1 in 1 Skip:3	17	10600
3	1 in 1 Skip:3	18	10700

3.1 Methods

The tested methods are Convolutional Neural Network (CNN) and Backpropagation Neural Network (BPNN). The flow of the events depicted in Figure 2 is as follows:

1. UAV was flown over the cotton fields. The images of them were saved on the hard disk inside the UAV;

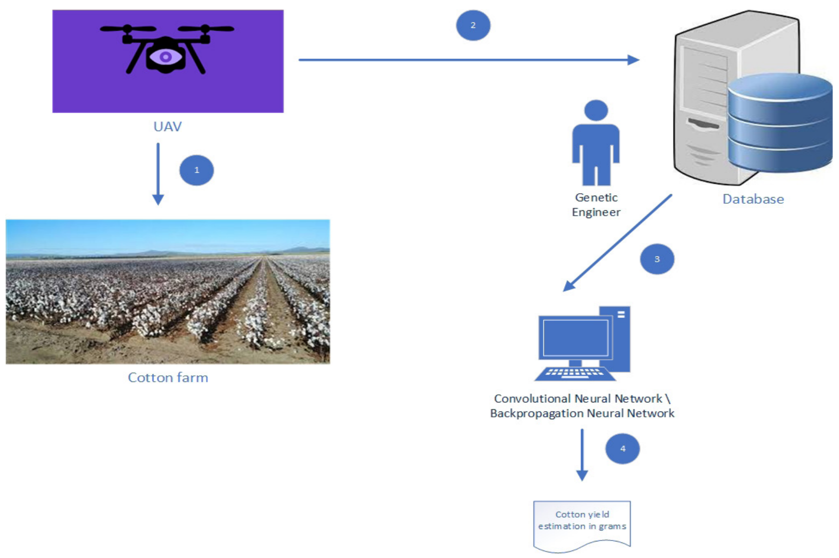

Figure 2. The process for estimating cotton yield in grams using an UAV and neural networks

2. Later, these images were transferred by the genetic engineer to a database server;
3. The trained CNN or BPNN were utilized to process these images;
4. Cotton yield in grams was estimated and displayed to the genetic engineer.

3.1.1 Method 1

A CNN is a type of neural network that has multiple layers and can achieve high accuracy while analysing UAV images for regression. CNN was first utilized in the field of processing images and time-series data (LeCun et al., 1989). The architecture of CNN is designed in such a way as to tackle the complexity of image pre-processing and process images in a different way and more effectively. They can automatically learn and extract the features and patterns from images by themselves, and later, utilize them to categorize data for classification or, as in this case, for regression tasks. In general, there are four different processing stages. The first stage is the convolution where feature values are obtained from input images using several image filters. The second stage is the pooling stage, where groups of "pixels" are "aggregated" and replaced by only one value (max, avg), which also results in a reduction of the spatial dimensions of the "image" passed further as input for the next layer. The third stage is the flattening stage where the two-dimensional feature set is converted into one-dimensional vector data and finally, that vector of data is conveyed as input to the next layer in the last stage for regression.

In the last stage for the feed-forward neural network, the cotton yields are estimated and the weights are updated using a backpropagation algorithm over one or more hidden layers (Goodfellow et al., 2016; Buduma & Locascio, 2017). CNN can pre-process the images such that the CNN designer does not have to figure out the feature vectors as in the case of classical neural networks. The CNN presented in this paper can find feature attributes by processing UAV images and use these features in estimating cotton yield. Various CNN models were tried using MATLAB and the most successful CNN among these models is depicted in Figure 3. The image size is 28 by 28 pixels. In the input layer, there exist batch normalization blocks as the 3rd, 7th and 11th steps. Each image is passed through three convolutional layers with 8, 16, and respectively 32 (3 x 3) filters each. The Rectified Linear Unit (ReLU) is used as the activation function at the end of each convolutional layer where the output of the ReLU is the maximum between the input value and the zero value.

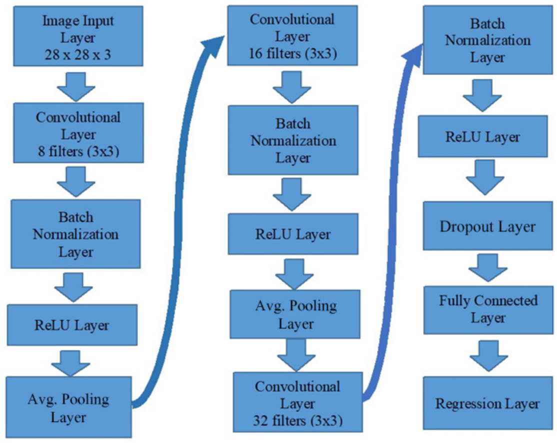

Figure 3. CNN architecture for estimating cotton yield

An average pooling layer was also utilized among the three above-mentioned convolutional layers , reducing spatial dimensions while the number of channels (filters) increased from one such layer to the next one. A dropout layer was also added before the fully connected layer to the CNN architecture to prevent the overfitting problem (Buduma & Locascio, 2017). A fully connected layer is utilized to reduce the two-dimensional data to one-dimensional data. This one-dimensional vector is utilized as the input to the fully connected hidden layer nodes the activation of which is linear. In the last layer, hidden nodes were connected fully to one output layer node, and the cotton yield was estimated at the end. The last layer is the regression layer instead of a classification layer, since classification deals with discrete class labels and categorical cross-entropy loss, while regression deals with continuous numerical values and employs absolute error loss. MATLAB R2017b was used to code this CNN. Finally, the output value denoted the final cotton yield estimation in grams (Goodfellow et al., 2016; Buduma & Locascio, 2017).

3.1.2 Method 2

The BPNN was designed to estimate the cotton yield amounts for the same UAV images (Figure 4). Two calculations were made for each UAV image to select the input features. The first calculation was carried out to find the mean values of red, green, and blue color components. The second calculation was carried out to find the standard deviation of each color component. Mean represents the average color properties inside an UAV image, and the standard deviation (Std) shows the amount of color deviation inside the same UAV image. As a result, each of the 600 images was represented with a feature vector [RedMean GreenMean BlueMean RedStd GreenStd BlueStd] (Figure 4). Moreover, color mean and std values were successfully used as selected features in (Unluturk et al., 2013). For the design of BPNN, the same feature values were utilized as in the case of CNN. According to Masters (1993), if there are m inputs, n hidden neurons and 1 output neuron in a neural network, there are (m x n + n) + (n + 1) unknown connections. To train such a network, at least 5 images are needed for each unknown connection. There are 480 images and 6 inputs, and the number of hidden neurons becomes 10. The activation function of the hyperbolic tangent (tansig(x)) was used in the second layer; in the last layer, the linear transfer function (purelin(x)) was used. The 480 UAV images were utilized for training the BPNN, and 120 images were used for testing the feed-forward neural network. After the testing, the number of correct values was found to be 106 out of 120 where the absolute value of the difference between the actual cotton yield value and its estimation was less than 350 grams. In the case of a BPNN, the designer typically needs to manually engineer or prepare the feature values that serve as input to the network. These features might represent specific characteristics or attributes of the data relevant to the task at hand. On the contrary, CNNs are well-suited for tasks involving images. CNNs can directly take in the raw image data as input, eliminating the need for manual feature engineering. CNNs automatically learn hierarchical representations of features from the raw pixel values, which can capture both low-level features like edges and textures and higher-level features like object shapes and structures. So, while BPNNs require pre-processing and feature engineering by the designer, CNNs can operate directly on the raw image data, making them particularly advantageous for tasks like regression. The next section presents the test results and their discussion with regard to the two employed methods.

4. Results and Discussion

Out of a total of 600 images, 20% were randomly selected for testing purposes and they were never included in the training phase. CNN was trained with 480 images and 120 images were used for testing. After the testing, a 95% accuracy was attained by the proposed CNN. The number of correct values is found to be 114 out of 120 where the absolute value of the difference between the actual cotton yield value and its estimation is less than 350 grams. In breeding studies, the genetic engineers are interested in the best cultivar that produces the highest yield. A tolerance of ± 350 grams indicates that estimations within this range are considered acceptable or within the norm by those genetic engineers. Figure 5 depicts a scattered

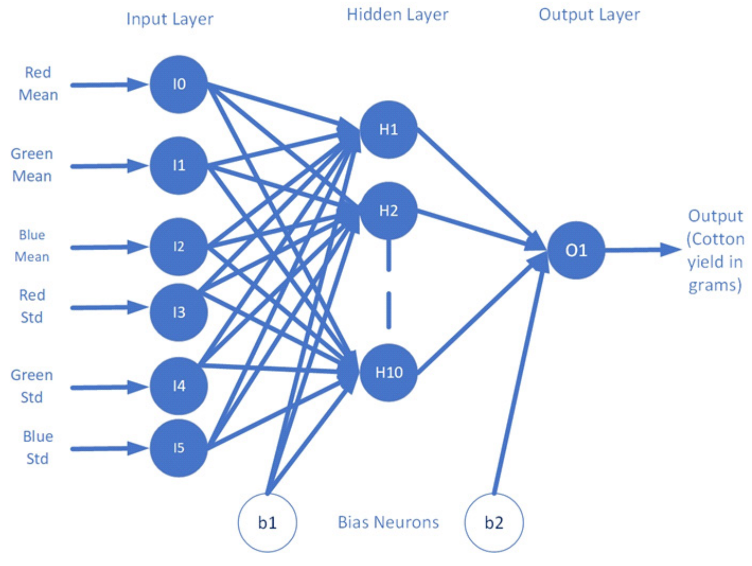

Figure 4. BPNN architecture for estimating cotton yield

chart where the x-axis includes the ground-truth yield values and the correspondent absolute errors in the predicted data for each of these values are displayed on the y-axis. One can see that that there are 6 test values over the 350 gram-threshold. The same training and testing images were utilized for the BPNN. Even though BPNN obtained a 88% accuracy, for capturing spatial features and the relationship among the pixels in the UAV images, CNN is a better method of the two. The CNN can discriminate different sections on an UAV image as well as specific features inside each section and try to find how these features co-existed within the same image. The CNN uses the same filter for each "channel" in a certain convolutional layer over those different sections of an image as it can be seen in Figure 3 to produce a feature map. This eliminates the manual feature extraction which is the fundamental part of the BPNN. As a remark, the CNN structure depicted in Figure 3 is a general one, which could be further utilized for other tasks / applications (for example to analyse infected food products) by taking the surface color and graphic shapes of the infected sections into consideration. Cotton variety development requires many field tests after obtaining an initial cross between two or more different varieties. These field tests should be carried out in different environments and at different time intervals to understand their adaptation and measure their genotype x environment (G x E) interaction effect. For many crops, the harvest is a more challenging and costly part of the field studies. As discussed in this section, the only alternative way as opposed to Method 1 (CNN) to estimate cotton yield in the early season was handpicking. In Method 1, the yield is harvested manually in a designated pilot area of the cotton field. Then the weight of the harvested yield is measured. The yield of the whole field is found by proportion. The cotton breeders need considerable labour usage. Obtaining this manpower and finalizing harvests before the rainy autumn season arrived are the other difficulties faced. During the harvest period, many plots need to be picked by hand and they have to be weighted after the harvest separately which also limits the variety testing capacity for cotton breeders. From the perspective of manual harvest (by hand-picking), providing labour, time and labour management creates pressure, limits testing capacity, and increases the cost of testing. Instead, if breeders can measure the yield potential of cotton varieties promptly with the help of UAV with CNN as explained in this study, they can both make more initial crosses and test up to hundreds of varieties. With this improvement at the testing level, the G x E interaction effect can be measured faster than manual harvest. Due to increasing testing capacity, breeders can check more varieties against changing weather conditions which are accepted as the main problem throughout the entire world today.

5. Conclusion

In this paper, UAV cotton field images taken from cotton fields in Torbali, Izmir, Turkey in 2019 were utilized for designing a CNN to estimate cotton yields. These images were fed into CNN and the corresponding outputs were the actual cotton yields in the training phase. For the training phase, 480 images were used and 120 images that were not part of the training phase were used to test the CNN's estimation accuracy. After the testing, a 95% accuracy was achieved by CNN. The number of correct values was found to be 114 out of 120

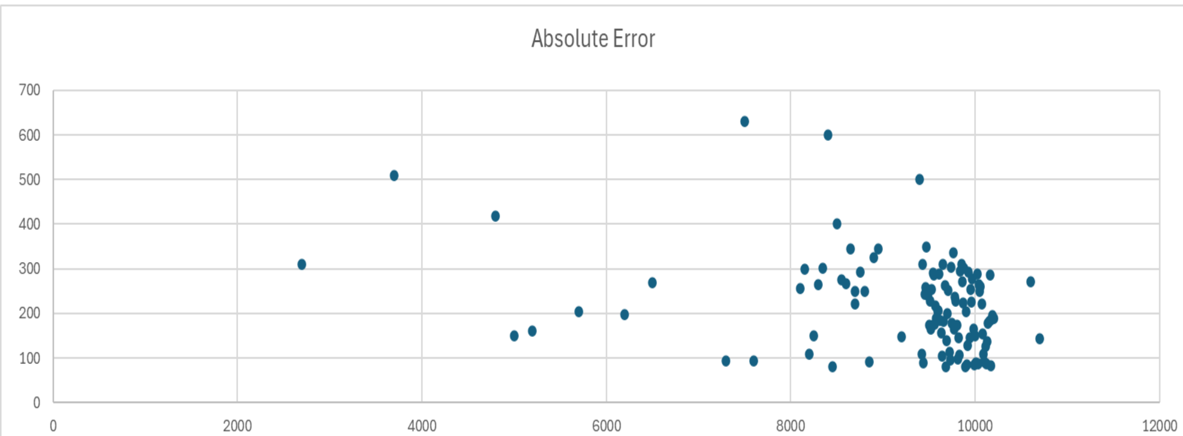

Figure 5. Scattered chart for absolute error vs ground-truth yield values

where the absolute value of the difference between the actual cotton yield value and its corresponding yield estimation value was less than 350 grams. This tolerance suggests that if the estimated yield value falls within ± 350 grams of the actual yield, it is deemed reasonable and acceptable by the genetic engineers. This margin allows for some variability or uncertainty in the estimation process while still maintaining an acceptable level of accuracy or precision. The designed CNN has been utilized in an international seed company, May-Agro Seed Corp. located in Bursa, Turkey. They have many test cotton fields, and they need to have farmer workers pick up the cotton to measure the cotton yields so that they can analyse each seed's potential. The cost of each worker is 30$ per hour. Picking up cotton physically and analysing it in terms of yield as well as fiber quality costs a lot of dollars for the seed companies thus limiting the number of new cross combinations and populations tested within a season. Instead, flying a drone is cheaper and processing the images with CNN is a very cost-effective and fast technique. The varieties with higher yielding can be detected easily and handpicked to run further analyses. This gives more freedom to the breeders to test more populations in a season and raises the chance of obtaining cotton varieties with the desired traits. In (Tedesco-Oliveira et al., 2020), the identification and classification of cotton bolls were made successfully by utilizing deep learning for images collected by a mobile device at different times of the day. The cotton yield estimation was done by counting the cotton bolls in those images. The methodology proposed in this paper was employed to predict the cotton yield by analysing the full image of the harvesting field instead of sections of it using the neural network model given in Figure 3. In (Huang & Thomson, 2016; Jung et al., 2018; Feng et al., 2020), UAV images are very effective tools and are used along with the vegetation indices to predict the cotton yields. Besides, a certain computational time and effort is necessary to determine the VIs for those images. On the other hand, the proposed novel neural network model can process those images within seconds.

The obtained results showed that the CNN (Convolutional Neural Network) can be effectively utilized in locating the cultivars with the highest yield. This neural network model can be used to make the yield estimation process shorter and more efficient. For a more accurate prediction, additional features can be added to improve the CNN, such as the normalized difference vegetation index (NDVI), plant height, canopy cover, and biomass. With these extra features and the addition of new images from planted areas, the CNN model can be retrained and possibly obtain even more accurate results.

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