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RESULT ANALYSIS FOR SUGARCANE QUALITY INSPECTION USING DEEP LEARNING

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Abstract: Uilized PC vision and deep learning methods to choose and plant sound billets, which expanded plant populace and the yield per hectare of sugarcane planting. We utilized notable convolutional neural network (CNN) structures to deal with enormous picture datasets and move learning methods to extend the outcomes to various sugarcane assortments. It would be extremely tedious to gather and mark huge datasets for every sugarcane assortment, for which quality investigation is required, preceding planting. We utilized a two-venture move learning interaction to stretch out the prepared design to new assortments. We looked at results got during move learning utilizing AlexNet, VGG-16, GoogLeNet, ResNet101 structures to traditional PC vision techniques. Our objective was to decide the best way to deal with identify harmed and great billets in the most brief preparing time. Best brings about both time and exactness were gotten with AlexNet. For AlexNet, we looked at stages of three sugarcane assortments to track down the best model to distinguish the sound sugarcane billets. We at that point diminished the quantity of pictures utilized to retrain the model to decide tradeoff among time and execution. Eventually, one requirements a couple dozen billets of the new assortment to retrain the network. Our methodology prompted significant augmentations in the yield per hectare going from 33 to 80% contingent upon sugarcane assortment

Keywords: *—Agricultural robotics, computer vision, convolutional neural networks, sugarcane, transfer learning..*

I INTRODUCTION

In increasing population has placed a greater demand on the Agricultural Industry to produce greater quantities of food. However, the number of individuals that actually produce food has continually decreased since. The 2017 Census of Agriculture reported a decrease in the number of farms, farmers, and farmland in the United States. The solution to this problem will require a combination of higher crop yields and an increase in crop production efficiency. Farmers will need to utilize technology to meet these demands and robotics may offer a significant part of this solution. Computer vision and image processing is a key aspect of many agricultural robotics applications like weed control, field scouting harvesting, yield prediction, etc. These applications encompass the combination of computer vision with Machine Learning techniques and, recently, Deep Learning approaches have grown in popularity with Convolutional Neural Networks (CNNs) being the preferred approach for detection and task recognition even in agriculture [5]. Here we use CNNs in a large image dataset to inspect and classify three sugarcane varieties.

Sugarcane is a tropical grass that grows worldwide and it is primarily used in sugar production. The total world sugarcane production in 2017 was 1,841,528,388 tonnes, which was produced on 25,976,935 hectares. When the farmers use mechanized combine harvesters to cut sugarcane into small segments, called “billets”, for planting, the billets are often damaged with cracks, crushed parts, or theirs buds are affected. Plant pathogens can enter through the damaged parts and adversely affect the sugarcane billets. Prior to mechanization of the planting process, one harvested hectare of seed cane would allow eight hectares to be planted. Post mechanization the damaged billets required doubling the planting density with estimates that one harvested hectare allows for the planting of approximately three to four hectares. The work in confirmed that damaged billets greatly impact the outcome in the planting process, significantly diminishing the productivity as the damaged billets could have been diverted to the mills for sugar production. Here we focus on expanding the inspection process of harvested billets with deep learning prior to planting.

There are many varieties of sugarcane. For example, in Louisiana there are twelve commercially grown varieties. These varieties are quite different in terms of dimensions and characteristics, making it difficult to detect the damaged features when employing a deterministic method developed for a single variety. Thus, it is important to develop a robotic solution using computer vision and deep learning to automatically detect the damaged billets, irrespective of the variety, and send them to the mills. To train and adapt the deep learning methods to detect the damaged billets, it is necessary to have a dataset with at least hundreds or even thousands of images for each new variety. The labeling necessary to train these methods depends on an exhaustive manual process done by experts in sugarcane to classify the billets according to the class of damage. It would be necessary to capture the images, preprocess them to the correct resolution, and then train the deep learning model while examining performance in estimation and detection tests to generate the final system to be used in real-time. This is quite a time consuming and costly process to repeat every time we have to classify a new variety. To address this limitation, we developed a two-step approach employing a CNN and transfer learning method to detect defects and outperform classical computer vision methods. Here we report on the approach: first, we performed an exhaustive comparative analysis on transfer learning of different CNN architectures to select the one that best detects the defect and second, we determined the minimum number of images required to expand and retrain the CNN.

CNN in agriculture was primarily employed in plant recognition, fruit detection (mainly on apples, sweet peppers, and mangoes), and weeding (mainly in sugar beet crops). The aforementioned literature focuses on detection of the whole fruit, plant, or weed. None of the writing is about quality inspection or detailed analysis of fruit or plant damage. For quality inspection, it is necessary to capture the images at a very short distance. There is some recent work on plant phenotyping using CNNs for specific features of wheat or other crops, and in identifying disease on the leaves of different plant species such as. We found very few papers on quality or detecting an immature fruit. The work in is the only one that made a quality analysis of sugarcane billets but was limited to only one variety and used classical computer vision methods, obtaining good results in the detection of the damaged billets but with high levels of false positives. To the best of our knowledge, our paper represents the first attempt on quality inspection of different sugarcane varieties using CNNs looking for damage introduced by combine harvesters.

Furthermore, most of these prior studies arbitrarily selected the CNN architecture. Two well-known CNN architectures widely used in agriculture are AlexNet and VGG-16 Others used the GoogLeNet architecture such as and ResNet with its different architectures. There were a few attempts to compare two, four, or even five different CNN architectures. Here we performed an exhaustive comparative analysis on transfer learning of four CNN architectures versus a classical computer vision solution. Our goal is to find the best performer in identifying most of the damaged billets while minimizing the number of samples so as to retrain the CNN with good performance for a new variety.

II DATA COLLECTION

We collected a large dataset of images, which served as the basis for all our experiments. Our dataset is publicly available at https://github.com/The77Lab/SugarcaneDeepLearning

Dataset : We collected a sample of different sugarcane varieties between September 24 and 26, 2018 in Houma, Louisiana, at the USDA Sugarcane Research Unit Farm. The team of sugarcane experts from the USDA included a Research Agronomist, a Biological Science Technician, two Agricultural Science Research Technicians, and a Biological Science Aid. The sugarcane varieties selected were: a) the L 01-299, which is the most widely grown variety in Louisiana by acreage; b) the HoCP 09-804, is a more recent variety than L 01-299, with greener and thinner stalks; and c) the HoCP 96-540, is an older variety with thicker stalks than either L 01-299 or HoCP 09- 804. Our experts suggested that HoCP 09-804 would likely be less damaged during harvesting because of its small size. Each variety was harvested in the early morning hours with a combine harvester, employing a wagon for transport.

III PROPOSED APPROACH

Deep Learning : Classical machine learning applications to task classification requires a lot of expert knowledge and manual fine-tuning to design the feature extractors that will classify the input images into the desired classes [4]. Deep learning is a form of machine learning that allows complex computational models to learn features in multiple layers. The most used deep learning method in computer vision is the Convolutional Neural Network (CNN) [4]. CNN is a type of Deep Neural Network (DNN) with different types of layers that creates different representations of the data from the most general to the most specific as the layers get deeper [5]. The learning process needs a training stage, which uses big datasets of images from which the network will learn the features. Usually only the last layers of the CNNs are fully connected, so that each layer can be trained with less interference. This improves speed. Depending on the number and type of layers, there are different CNN architectures. Instead of arbitrarily selecting a popular CNN architecture, we performed a comparative analysis of several CNN architectures applied to our problem to detect the quality of the sugarcane billets. We selected the four most used CNN architectures in agriculture: AlexNet created by Krizhevsky [25] (with a depth of 8 and 25 layers in total), VGG-16 developed by Simonyan and Zisserman [26] (with a depth of 16 and 41 layers in total), GoogLeNet made by Szegedy et al. [27] (with a depth of 22 and 144 layers in total), and ResNet generated in all its versions by He et al. [28] (we are using ResNet101 with a depth of 101 and 347 layers in total). Those four CNN architectures cover a wide spectrum of models from a few layers to many and different depths among other characteristics.

Transfer Learning : In classical machine learning, we would need to train the system every time with a new dataset, which is not efficient and takes too much time (see an example for 3 varieties in Fig. 2 a). Transfer Learning, also known as Knowledge Transfer, is used to reduce the need and effort to collect the labeled dataset or augment it [29]. In many real-world applications, it is expensive or impossible to collect large datasets for all possible classes. Transfer learning improves the learning of a new task through the transfer of knowledge from a related task that has already been learned. In the case of the four popular CNN architectures selected, they were already pretrained with more than one million images of around 1000 classes [30]. Even when those classes are different objects --e.g., vehicles, animals-- the models are very useful to extract features on the images and the retraining of these models is done in a much shorter time. We modified the last fully connected layer of each of the four architectures (AlexNet, VGG-16, GoogLeNet and ResNet101) to have only two neurons (instead of 1000) that represent our two classes. Instead of training the models from scratch with our datasets, those four pre-trained popular models could be used to improve the learning (as depicted in Fig. 2 b). However, it would be necessary that experts manually classify hundreds if not a thousand sugarcane billets every time to retrain the CNN model. This would not be practical in the field as it would be time intensive. Instead, we propose to take advantage of Transfer Learning in two steps to create an automatic process that could allow any farmer to In the first step, we transfer the knowledge obtained by AlexNet, VGG-16, GoogLeNet or ResNet101 to the task of sugarcane quality detection. The dataset of a sugarcane variety is used to retrain the selected CNN architecture. As a second step, a new CNN model is retrained with a new dataset of another variety to transfer the learning to that one. We ran the tests for all permutations of the three harvested sugarcane varieties. The first step was done for all four CNN architectures, each architecture with each of the three sugarcane varieties. From there, the model that had the highest values of TNR (True Negative Rate used for all the correctly classified defective billets), of TPR (True Positive Rate used for all the correctly classified healthy billets), and of MCC (Matthews Correlation Coefficient used for the overall calculation) to increase productivity and reduce processing time to train and test was chosen. MCC is a statistical score typically employed for binary classifications of unbalanced datasets (our case) [31]. use it for any sugarcane variety (see Fig. 2 c).

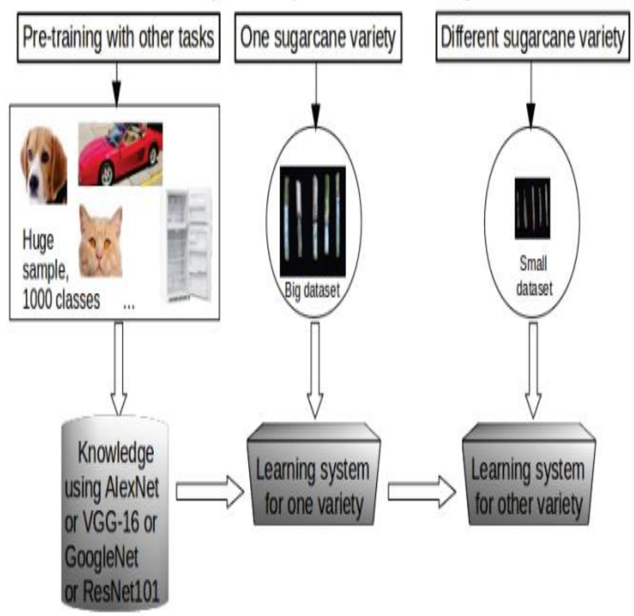

Fig 1. Proposed System

MCC is a better choice than others, such as the ACC (Accuracy commonly used in CNNs in agriculture), because it has a high value only if true positives, true negatives, false negatives, and false positives had good results. The MCC ranges between -1 (worst prediction) to 1 (best prediction), where an MCC of 0 indicates that the prediction could be obtained randomly. The second step was made only for that chosen model. In other words, we repeated six times the flow shown in the bottom of Fig. 2 for the chosen CNN model.

IV ANALYSIS

Experts determined the appropriateness of sugarcane billets for planting. We then trained different CNN architectures to identify the billet quality. After this training that data is tested as actual values of the billets and predicted values of the billets are matched with each other. In that analysis the both are matched mostly so accuracy of the system is good.

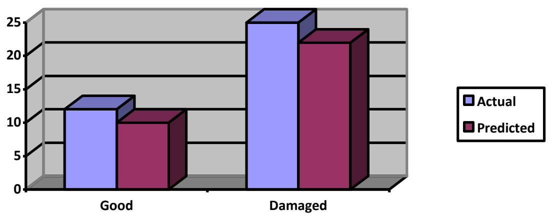

Fig 2 System Analysis

V CONCLUSION

We demonstrated that the use of deep learning delivers much better results in terms of performance than the classical computer vision method. We doubled the performance for L 01- 299 variety; quintupled the performance for the HoCP 09-804 variety, and got a much superior result for the HoCP 96-540, for which the classical method did not work well. The popular CNN models (AlexNet, VGG-16, GoogLeNet and ResNet101) are pretrained with very large datasets, which helps to retrain faster to obtain better results. As the layers of the CNN models increase in number, the processing time increases rapidly. Hence, there is a tradeoff between a processing time and performance. Among the models that were compared, AlexNet proved to be the best option to perform quality inspection on sugarcane billets. AlexNet was implemented in a two-step process of transfer learning and led to around 22 times less billets to retrain the network for a new sugarcane variety. Every time it is necessary to harvest and plant a new sugarcane variety, a farmer could quickly classify a minimum number of billets of the new variety (around 50 billets) and retrain the system leading to improvements of 33 to 80% as compared to without the system. Deep learning, specifically AlexNet CNN and transfer learning in two steps, may allow a farmer to classify the quality of the sugarcane billets and afford planting ~7 new hectares of sugarcane instead of the present 4 hectares. One must take our results with the appropriate caveats. There might be errors due to preprocessing manual tasks at the beginning of data collection. We plan to account for these errors in future estimates of the performance

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