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Identifying Wheat Breed Genotype Using CNN & LSTM

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ABSTRACT:
Image processing has been applied to various process of agriculture industry in order to achieve fast and accurate operation. applying image processing techniques to classify wheat seeds based on their varieties is also objective method in real time applications can provide additional knowledge in their production, seeds quality control and in impurities identification. Also, it is very important to confirm the variety of the wheat before planting. Because each variety needs its own condition for taking good yield. In this study, a method is proposed to identify the varieties grown by using image analysis techniques, with the motivation of developing a fully automatic grain type and variety identification system. the sun pest is a major threat to agriculture, as it damages some of the most important crop varieties. this distinctive characteristic makes the datasets especially suitable for application such as sun pest damage detection and grain segmentation. Since the dataset includes various cultivars, it is also appropriate for segmentation.

KEYWORDS: deep learning, convolutional neural networks, long short term memory, wheat, genotype identification.

INTRODUCTION:
Seed analysis and classification are carried out to obtain information regarding the seed type, variety, quality, and production. seeds that are pure, free from insects are considered high quality seeds. Identifying the type, variety, and quality of seeds is essential for certification purposes. It also represents the initial step in seed processing operations used in separation machines. The use of certified seeds helps improve both quality and quantity of crop yield.
Generally, seed analysis and classification for certification are performed by experts through visual inspection of seed characteristics. However these traditional methods are time-consuming, labor intensive, expensive, and highly dependent on human judgement. In seed separation machines, process such as determining seed properties, identifying seed types and varieties, and detecting diseased or structurally damaged seeds are conducted. In modern seed machines, these operations are performed using mechanical methods along with optical techniques. Seed analysis and classification are typically carried out by experts through visual examination of seed characteristics.
In such machines, seeds are directed to move through a channel capacity becomes a key parameter in the overall operation. To improve processing efficiency, accurate detection of seed disease is also crucial from the perspective of both producers and consumers. Therefore, during the separation process, it is desirable

to identify seed varieties and detect diseased or structurally deformed seeds without increasing the channel capacity.
For these reasons, many agricultural applications have been automated in recent years, and the use of image processing techniques has gained significant importance. Compared to conventional methods, image processing offers several advantages, including the ability to design fully automated systems. This approach provides objective solutions for real time identifications of wheat varieties and enables non-contact operation. the development of new wheat varieties has significantly improved the efficiency of the wheat industry, these programs have also led to frequent mixing among different wheat varieties is an efficient, simple, and accurate manner has become a critical issue.

LITERATURE REVIEW:
The application of deep learning, machine learning, and image processing techniques across several fields has been greatly aided by recent developments in intelligent systems. [1] A hybrid deep learning framework for fault classification in power transmission lines was proposed by Xue Han and Yu Wang. The system still needs to be improved for real-time deployment and scalability in large power infrastructures, but the integration of multiple models allowed for improved detection accuracy under varying operational conditions. [2] Zihan Yin investigated grid fault detection using an image processing technique based on CNN-LSTM and CVPFI, which successfully captures both spatial and temporal features to improve fault identification. However, the method has issues with processing speed and computational complexity. [3] Although the model's performance may vary depending on user diversity and environmental conditions, Shiva Mehta and Sumeet Singh Sarpal introduced a machine learning-based system for tracking leg exercises in fitness environments using a CNN-LSTM architecture, enabling real-time tracking of human movements to improve safety and prevent injuries. [4] In order to identify vertical oil-in-water flow patterns, Niu Xiangyang and Yiyang created a CNN-LSTM framework based on deep learning and image processing. This framework showed a strong ability to recognize complex flow behaviors, but it also indicated the need for improved robustness against noise and industrial variations. [5] An image processing-based CNN-LSTM method for detecting low-resistivity reservoir fluids was proposed by Xiangyue Chen and Senlin Yin. This method achieved dependable detection even in difficult geological conditions, but more improvement is required to improve efficiency and adaptability for large-scale real-world applications.
In recent wheat breeding research, deep learning techniques particularly convolutional neural networks and log short term memory networks are widely used for the identification of wheat genotypes. these methods significantly enhance traditional breeding and seed classification processes. convolutional neural networks are mainly applied to extract spatial features from wheat grain images, while hybrid models that integrate long short term memory networks utilize temporal or sequential information, resulting in higher classification accuracy.
Hybrid convolutional neural networks and long short term memory models combine the strength of convolutional neural networks in capturing short range dependency patterns from image encoded genomic sequences with the capability of long short term memory to model long term dependencies among gene loci. This integration has demonstrated competitive performance in predicting agronomic traits and crop yield. In such as xception to bi long short term memory have achieved high accuracy levels by processing both visual and sequence based grain features. convolutional neural networks based approaches, including resnet, are also employed to classify wheat cultivars across different growth stages, improving

identification accuracy from seedling to flowering phases.Despite their effectiveness, deep learning models are computationally intensive and require substantial memory resources and powerful GPUs for training. They also depend on large, well automated, and diverse datasets to reduce overfitting risks.
However, these approaches face limitations due to their black box nature, which makes interpretation difficult for plant breeders. Additionally, they are sensitive to high variance data, including changes in lighting conditions, soil background, and environmental factors. long short term memory networks are particularly suitable for handling sequential and temporal data beyond image processing. They have been effectively utilized in time series agricultural analysis, such as longitudinal crop growth monitoring and genotype specific behavioral studies.

PROPOSED METHOD

Which combine convolutional neural networks and long short term memory these networks are analyze genomic data. This main of the role it approaches aim to capture both local and global dependencies in wheat genomic sequences for improved genomic selection.

1. WHEAT IMAGES DATA ANALYSIS

The wheat image data of this varieties are all main stream varieties. the image data collection time for the wheat tillering period was mostly to have time for five to fourteen days. there were three sunny days, three cloudy days, two days of light rain, two days of cloudy. The moisture content of all seeds at the time of shooting was between 7.5-10%. Parts of the tillering stage, and seed images are shown in the figure. In the shooting process, various weather conditions and natural lighting condition were included, which increased the diversity of the captured images. The 30 selected wheat varieties are all mainstream winter wheat varieties. approximately30 plants were selected for each variety. And images were taken from multiple angles and aspects. Such as top, side, distance, height, whole, and part. A total of images were collected and the tillering stage, about 1000 for each variety. The size of the pictures was mainly six hundred into twelve hundred pixels, and the naming method was “wheat variety abbreviation”, “plant number”, “camera view number”.

2. NETWORK STRUCTURE DESIGN

Based on transfer learning. In this paper combines the resnet, se-resnet, se-resnext, models, and the proposes a cmpnet model improve the accuracy of the models identification of wheat varieties. the number of parameters of these four models are as follows: cmpnet has parameters, resnext has twenty five parameters. This model has a symmetrical structure along the horizontal direction. The model has three input terminals: pictures of the wheat tillering stag. Pictures of the wheat seeds. Since the wheat sees were small, 30 wheat seeds were placed on a blue purple background in a 5 into 6 format.

3. DATA PREPROCESSING AND ENHANCEMENT

To ensure the stability of the model during operation. Reduce the models dependence on some irrelevant features and improve the generalization ability of the model, data processing was required. In the original image, the storage space of a single image at either the flowering stages of wheat was about 600KB. And an image was image was about 4MB. Enhancing the image while ensuring the data feature information is retained can also increase the amount of training data.

SYSTEM ARCHITECTURE

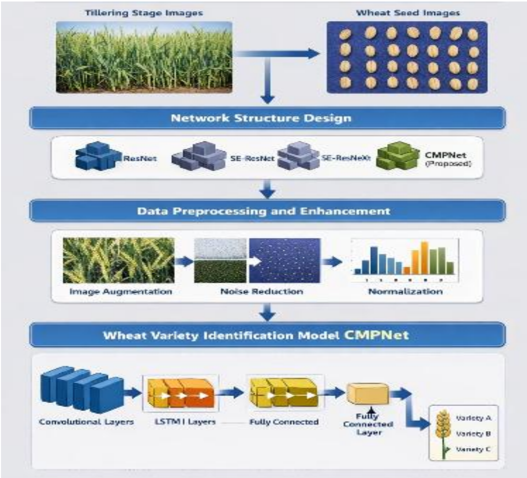

FIG 1. SYSTEM ARCHITECTURE

RESULT AND DISCUSSION

The loss number and accuracy of the model training process as number of training iterations increased. As the number of training iterations increased, the training loss rate showed a downward trend. Although the loss rate in part of the training phase did not decrease but rather increased, the overall loss rate was in a declining state and quickly converged, and finally oscillated at around0.08 without decreasing.
Furthermore, as the number of training iterations increased, the training accuracy rate also increased. When the number of iterations reached about 1100, the model was very close to the optimal solutions in the space, and the training accuracy also tended to converge. Since the piecewise decay learning rate was used, each piece wise learning rate could allow the optimization to proceed to a start where the weight vector distribution was relatively stable, in order to obtain a better local minimum.

GRAPHS

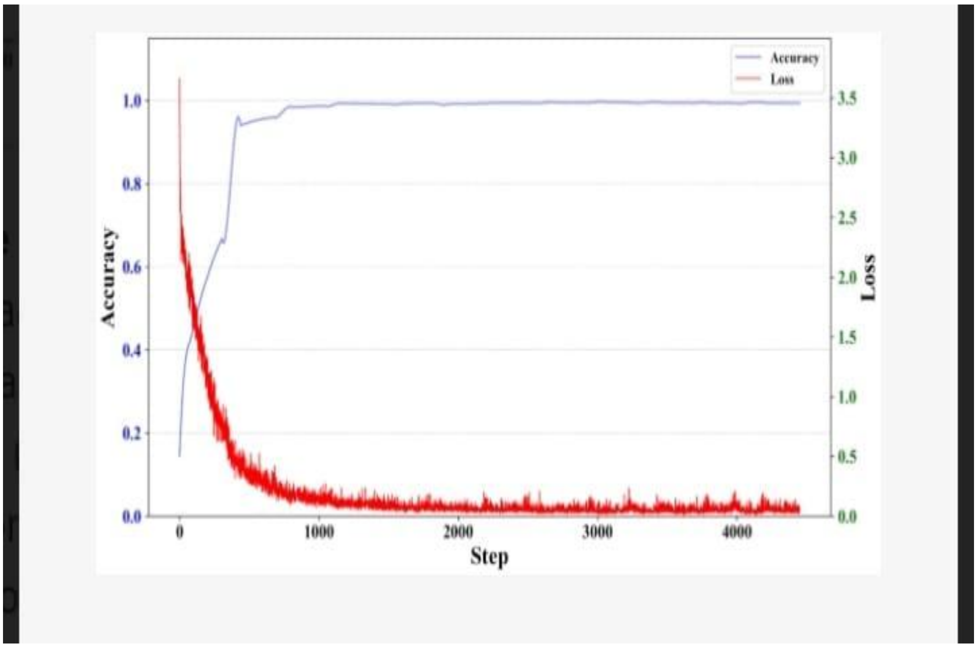

FIG 2. ROC GRAPH

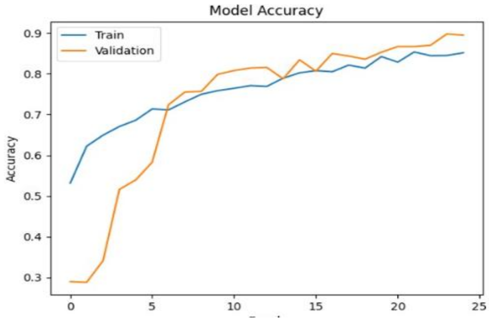

FIG 3. MODEL ACCURACY

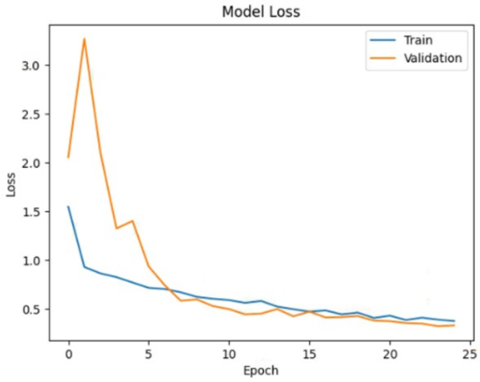

FIG 4. MODEL LOSS

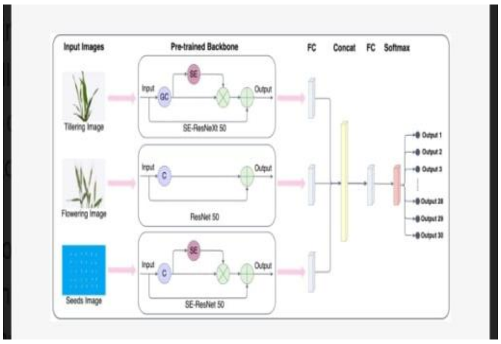

FIG 5.TRAINING

SCREENSHOTS

FIG 5. DATASET

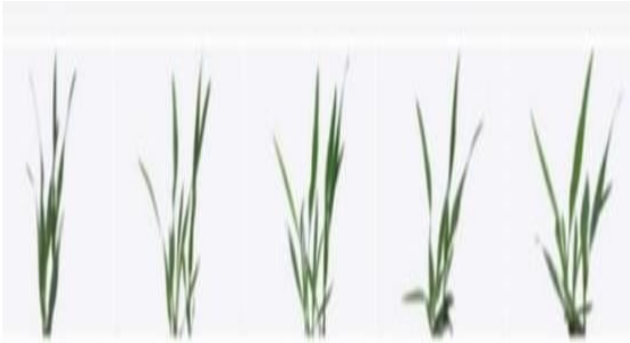

FIG 6. TYPES 1 OF WHEAT

FIG 7. TYPE 2

FIG 8 INDEX PAGE

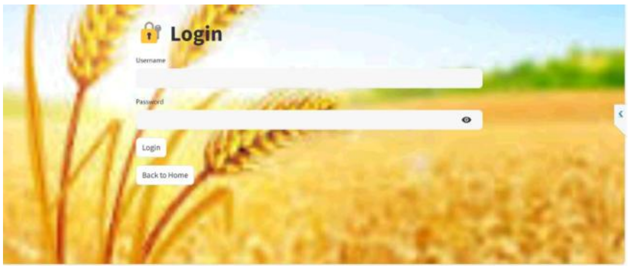

FIG 9.LOGIN PAGE

FIG 10. UPLOAD PAGE

FIG 11. PREDICTION RESULT PAGE

CONCLUSION

This paper proposes a identification model based on image processing with images of growth periods of wheat. Taking the image data as the core, based on the transfer learning method of the se- resnet, resnet, and se-resnext, models, image recognition models for the heat tillering stage, wheat flowering stage, and wheat seed were constructed respectively, then the models for the heat tillering stage, wheat flowering stage, and seed were constructed respectively, then the models were combined to improve the accuracy and generalization ability of the model. The method uses migration learning, and some local optimal solutions stored in the pre-training parameters do not need to be retained, reduced the model training time and cost. The training dataset contained images of different growth periods of wheat, which solved the problem of the single characteristics of wheat and ensured the reliability of the model. Our future work will mainly be divided based on four considerations: the interaction of biological genes and environment means the same crop variety may present different production environments. In order to give full play to the models advantages in classification speed and accuracy. We will deploy the model to portable electronic terminals like mobile phones to realize rapid and timely classification of the photos we take in the future, with which the models superiority will be fully displayed.in the view of the generally poor recognition rate of wheat seeds, our follow up research will collect more data and improve the model algorithm according to the various characteristics of wheat. The recognition accuracy for a single growth period of wheat should be improved, and we will consider transplanting the model to the variety recognition of other crops.

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