MOBILE APPLICATION TO DETECT SUGARCANE DAMAGED BILLETS

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ABSTRACT

Sugarcane plays an essential role in global agriculture due to its significance in the production of sugar, ethanol, and bagasse. Modern sugarcane cultivation often relies on billets, making it imperative to maintain healthy billets for optimal yield. However, the use of harvesting machines introduces the potential for billet damage, which can lead to disease spread and reduced quality. Developing a robotic solution that employs computer vision and deep learning to detect the damaged billets is important. Conventional methods for damage detection are hindered by complex backgrounds, necessitating the development of an efficient model for sugarcane billet damage categorization.

The work presents the Sugarcane Billet Damage Detection App, which integrates advanced image processing techniques and the FDHOA-based DMN model. The applications user-friendly interface includes informative content on sugarcane cultivation and a robust billet damage detection feature. The FDHOA-based DMN model, leveraging fractional calculus and optimization algorithms, achieves remarkable accuracy in categorizing sugarcane billet damage, contributing to more efficient and intuitive sugarcane harvesters.

Keywords: Crop disease classification, Sugarcane billet damage, Fractional Calculus (FC), Deer Hunting Optimization (DHO) algorithm, Deep Maxout Network (DMN).

INTRODUCTION

The 2017 year recorded a decline in the quantity of farms, agriculturalist and farming land across the United states[11]. Addressing this issues will necessitate a blend of enhanced crop productivity and heightened efficiency in crop cultivation. Farmers must employ technological advancements to fulfil these requirements, with robotics potentially constituting a significant component of this solution. The utilization of computer vision and image processing stands as a pivotal facet in numerous agricultural robotics applications[12], including weed management, field management, harvesting, and yield estimation. These functionalities entail the fusion of computer vision with various machine learning methodologies[13], with deep learning methodologies, particularly convolutional neural networks(CNNs), gaining traction for detection and task identification [14]. even within the realm of agriculture [15].

Sugarcane cultivation stands as a cornerstone of agriculture on a global scale, offering essential raw materials for diverse industries. The total world sugarcane production recorded in 2017 was 1841528388 tons, which was produced on 25976935 hectares of land [16]. While the introduction of sugarcane billets has enhanced cultivation practices, it has simultaneously introduced the risk of billet damage during the harvesting process [17].

This work introduces the Sugarcane Billet Damage Detection Application, a pioneering solution that seamlessly combines user authentication, comprehensive information on sugarcane cultivation practices, and a robust billet damage detection system. At the heart of this application lies an deep learning model known as the Fractional Deer Hunting Optimization Algorithm-based Deep Maxout Network (FDHOA-based DMN) [10]. This model revolutionizes the accuracy and sensitivity of sugarcane billet damage categorization.

LITERATURE SURVEY

A state of the art literature review of existing papers is been carried out. Devayani Suryavanshi, et al. [1] developed a computer vision model for efficient classification of sugarcane billet damages. A prototype model was designed to categorize the healthy billets from the damaged billets so that the healthy billets can be considered for planting. This method effectively separated the healthy and damaged billets and also increased the effectiveness of sugarcane planting. In addition, rings, buds, or any damage on the sugarcane billet was easily identified using this prototype model. This model incured a high computation cost.

Moises Alencastre-Miranda et.al [2] have discussed a two-step approach that employs a CNN and transfer learning method that out performs the classic computer vision methods to detect defects. Here they report an approach where in they perform an exhaustive comparative analysis on the transfer learning of different CNN architectures to select the one that best detects the defects , and then determine the minimum number of images required to expand and retrain the CNN. They have selected the four most used CNN architectures in agriculture: AlexNet with a depth of 8 and 25 layers in total, VGG-16 developed with a depth of 16 and 41 layers in total, GoogLeNet with a depth of 22 and 144 layers in total, and ResNet. Hence, the model should maintain a better trade-off between processing time and performance of the model, Even though the approach achieved superior results, increase in the layers of CNN model increased the processing time drastically.

Andrew Busch et.al [3] developed an effective model that maps the sugarcane billet density using deep learning techniques and object detection. A camera was located under the planter to analyse the sugarcane billet damage utilizing a YOLOv3 framework. This method provided a good quality machine vision system. However, the method was not capable to analyse all type of sugarcane diseases.

Wen Chen, et al. [4] designed an algorithm for object detection using deep learning approach that can recognise sugarcane stem node. Here, YOLOv4 network was presented to analyse the crops in complex natural environments. The robustness and generalization ability of this method was high under various illumination circumstances. The images were gathered from diverse lighting circumstances, such as side light, forward, and back light. This method achieved high robustness and was twice as fast as that of YOLOv3 network on a clear background. However, the cost required for implementing this method was high.

Md. Shahin Sharif, [5] developed Convolution Neural Network (CNN) model for effective sugarcane disease detection and classification. This research tested and trained the deep learning approach comprising of 2200 sugarcane image datasets. This model facilitated the framers with the incredible function of deep learning technique in recognizing and categorizing the sugarcane infections.

Arun A. Kumbi et al. [6] have developed a deep convolutional neural network algorithm based on sunflower atom optimization to provide optimal water control in sugarcane. However, this method was not considered for the damage occurring in the sugarcane.

R. Ramani, et.al [7] primarily focus on the pre-processing stage as it is more application dependent and can enhance the content of medical image based on removal of special markings and speckle noise by which the quality of image segmentation is enhanced. This also improves the accuracy and efficiency of content based medical image classification and retrieval systems. The work focuses on four types of filtering techniques on mammography images. They have compared the simulated output parameters such as image quality, mean square error, peak signal to noise ratio, structural content and normalized absolute error.

Lingfei Yan, et.al [8] This paper results prove that PSP Net has the highest segmentation accuracy rate of 0.9865, over-segmentation rate of 0.0023 and under-segmentation rate of 0.1111, which is less than FCN and U-Net, which greatly improves the accuracy of model judgment. The ROC curve of PSP Net is closest to the upper left corner, and the AUC is 0.9427, which is greater than FCN and U-Net. It is verified that the obtained model has a better discrimination effect.

Gaurav Agarwal et.al [9] This work focuses on a optimized classifier DNN-DHO for speech regognition .The datasets used are TESS dataset and RAVDESS dataset for English speech and IITKGP-SEHSC dataset for Hindi speech. The experimental results are compared with DNN_DHO, DNN and DAE classifiers using the three datasets. The results have shown that the DNN-DHO method gives a better result when compared with the other classifiers. The results achieved with the TESS dataset, RAVDESS dataset and IITKGP-SEHSC dataset with highest accuracies of 97.85%, 97.14% and 93.75% respectively.

Arun A. et.al [10] where a classifier is designed as FDHOA. The developed classifier classifies the sugarcane billet damage into six different classes as cracked, crushed, no buds, two buds, single damaged bud, and no damage. Additionally, the proposed FDHOA-based DMN has obtained high testing accuracy, sensitivity, and specificity with the measures of 0.938, 0.926, and 0.955 when the training data is 90%.Moreover, while considering K-fold value is 5, the FDHOA-based DMN has obtained high testing accuracy, sensitivity, and specificity of 0.937, 0.933, and 0.952 respectively when compared to the existing approaches such as YOLOv3 network, Deep learning, Deep NN, and CNN.

Proposed FDHOA-based DMN Model

An innovative approach has been devised to categorize sugarcane billet destruction, utilizing a newly designed methodology known as FDHOA-based DMN. This sophisticated model excels at classifying sugarcane billet damage into six distinct classes. The classifier undergoes rigorous training through the utilization of the specially crafted FDHOA [10].

- ***Pre-processing Using Median Filtering***

The input image, denoted as Di, undergoes crucial pre-processing to eliminate external noise and artifacts. Pre-processing plays a pivotal role in rendering the image suitable for subsequent analysis while simultaneously enhancing its quality. Median filtering [18], a widely employed order-statistics filter in image processing, is leveraged in this step. This technique effectively eliminates noise from the original image while preserving the integrity of significant data. By replacing each pixel with the median value of its neighbouring pixels, median filtering minimizes sensitivity to outliers, thus ensuring noise reduction without compromising image quality. The result of this pre-processing step is represented as Pi.

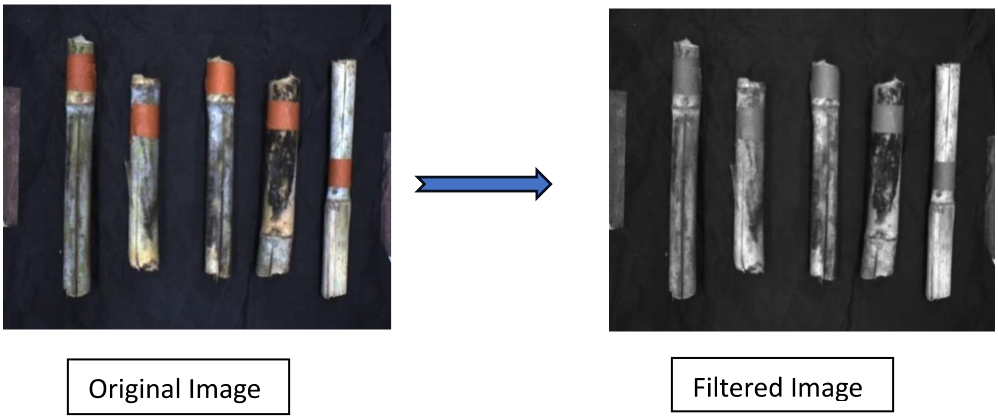

Fig.1 Median Filtered image

- ***Segmentation Based on PSP-Net***

Once the pre-processing is executed with precision, the sugarcane billet image undergoes segmentation via the Pyramid Scene Parsing Network (PSP-Net). The PSP-Net is equipped with a pyramid pooling network that effectively addresses the limitations of classical structures in capturing global information. While global average pooling has proven effective, it falls short when dealing with complex datasets. PSP-Net's selection for image segmentation stems from its cost-effectiveness and computational efficiency. Notably, the combination of PSP-Net and pyramid pooling minimizes computational expenses without compromising segmentation quality. The PSP-Net framework is shown in Fig.2 [8].

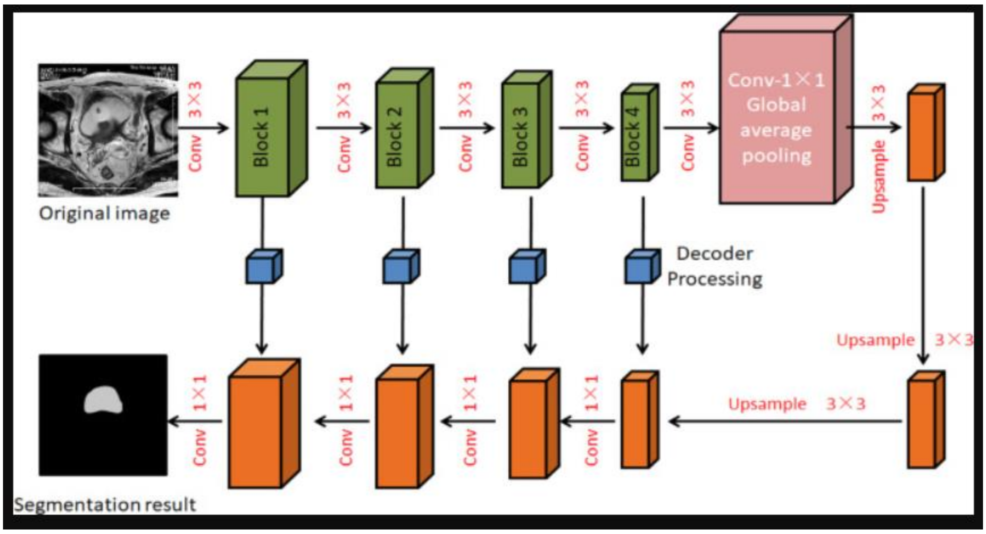

Fig.2 PSP- Net framework

- ***Sugarcane Billet Damage Classification Using DMN***

The subsequent crucial step involves the classification of sugarcane billet damage, a significant process that directly impacts crop yield. Billets are smaller portions of each sugarcane stalk, that are commonly used in the harvesting process. Thus, analysing damaged sections of sugarcane billets is essential for optimizing the harvest by identifying and removing damaged portions. In this research, billet damage categorization is achieved through the application of DMN. DMN excels in classifying segmented images with remarkable accuracy, all while maintaining low computational complexity. The DMN categorizes sugarcane billet damage into six distinct classes: cracked, crushed, no buds, two buds, single damaged bud, and no damage.

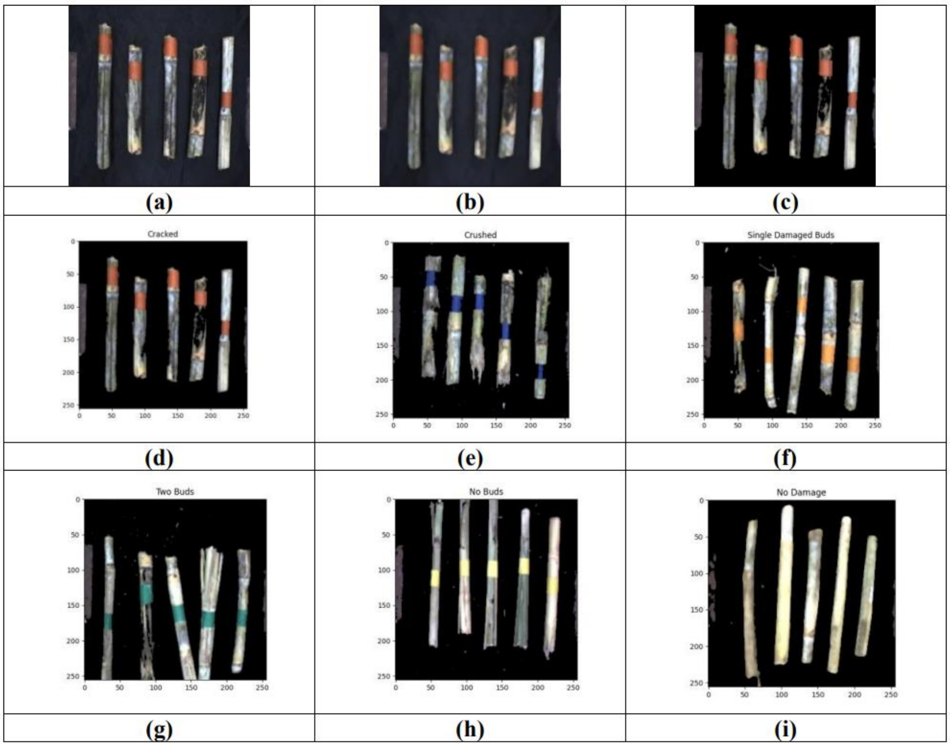

Fig. 3 Experimental outcomes, a) Input image, b) Pre-processed image, c) Segmented image, d) Cracked class, e) Crushed class, f) Single damaged buds class, g) Two buds class, h) No buds class, i) No damage class

- ***Proposed Fractional Deer Hunting Optimization Algorithm (FDHOA)***

The DMN classifier is meticulously trained using the FDHOA [10], a novel optimization algorithm that merges the strengths of two potent techniques: Deer Hunting Optimization Algorithm (DHOA) and Fractional Calculus (FC). DHOA, inspired by the hunting behaviours of human hunters tracking deer, is a metaheuristic algorithm. It leverages the concept of a leader-follower hunting strategy, wherein hunters continuously adjust their positions to approach the target. DHOA's optimization challenge lies in accounting for various deer characteristics, including their exceptional visual acuity and sensitivity to specific colours and movements. FC, on the other hand, bolsters computational efficiency. By integrating the characteristics of both DHOA and FC, the proposed FDHOA-based DMN model attains superior results, combining rapid convergence with optimized solutions. This innovative fusion enhances the effectiveness of the classification process and offers more optimal solutions for complex optimization problems.

The Sugarcane Billet Damage Detection App represents a transformative leap in sugarcane cultivation technology, integrating cutting-edge deep learning techniques such as FDHOA-based DMN to accurately categorize billet damage and optimize crop yield.

METHODOLOGY

- **Deep Learning Model Preparation**

Algorithm Selection: The methodology begins with the selection of an appropriate algorithm for billet damage detection. In this case, the Fractional Deer Hunting Optimization Algorithm-based Deep Maxout Network (FDHOA-based DMN) is chosen due to its effectiveness in categorizing sugarcane billet damage.

Dataset Collection and Preparation: A comprehensive dataset of sugarcane billet images is collected and prepared for model training. This dataset includes diverse examples of billet damage types to ensure model robustness. **https://www.kaggle.com/datasets/ashutoshsoni06/sugarcane-billet-dataset**

This dataset includes six classes and the class labels include, cracked, crushed, no buds, single damaged buds, two buds, and no damage.

Model Architecture Design: The architecture of the FDHOA-based DMN is carefully designed, specifying the number of layers, neurons, activation functions, and other architectural parameters. This design phase aims to create a model capable of accurate damage categorization.

Model Training: Using the prepared dataset, the DMN model is trained using deep learning frameworks such as TensorFlow and PyTorch. During training, the model learns to categorize sugarcane billet damage into the desired classes. Fig. 4 is a snippet of the model training that is been carried out.

```
In [28]: import os
import cv2
import numpy as np

# Set the root directory of the segmented images
segmented_folder = './segmented_images'

# Set the output directory for the classification results
classification_folder = './classification_results'
os.makedirs(classification_folder, exist_ok=True)

# Define the DMN classification classes
classes = ['cracked', 'crushed', 'nobuds', 'singledamagedbud', 'twobud', 'nodamage']

# Process each image in the segmented folder and its subfolders
for root, dirs, files in os.walk(segmented_folder):
    # Create corresponding subdirectories in the classification folder
    classification_subfolder = os.path.join(classification_folder, os.path.relpath(root, segmented_folder))
    os.makedirs(classification_subfolder, exist_ok=True)

    # Process each file in the current directory
    for file_name in files:
        if file_name.startswith('segmented_'):
            # Set the input and output paths
            input_path = os.path.join(root, file_name)
            output_path = os.path.join(classification_subfolder, file_name.replace('segmented_', ''))

            # Load the segmented image
            segmented_image = cv2.imread(input_path, cv2.IMREAD_GRAYSCALE)

            # Perform DMN classification
            # Replace the following code with your own classification algorithm
            # Here, we simply assign a random class label
            class_index = np.random.randint(len(classes))
            classification_result = classes[class_index]

            # Save the classification result
            with open(output_path, 'w') as f:
                f.write(classification_result)

            print(f"Classification result saved: {output_path}")
```

Fig.4 Model Training

```
In [4]: split_directory = './split'

# Create TensorFlow Dataset objects for training and validation
train_data = tf.keras.preprocessing.image_dataset_from_directory(
    directory=os.path.join(split_directory, 'train'),
    batch_size=32,  # You can adjust the batch size as needed
    image_size=(224, 224),  # Adjust the image size to match your model's input size
    shuffle=True,  # Shuffle the training data
    seed=42,  # Random seed for reproducibility
    validation_split=None,
)

validation_data = tf.keras.preprocessing.image_dataset_from_directory(
    directory=os.path.join(split_directory, 'validation'),
    batch_size=32,  # You can adjust the batch size as needed
    image_size=(224, 224),  # Adjust the image size to match your model's input size
    shuffle=False,  # Don't shuffle the validation data
    seed=42,  # Random seed for reproducibility
    validation_split=None,
)

# Optionally, configure prefetching for better data loading performance
AUTOTUNE = tf.data.AUTOTUNE
train_data = train_data.prefetch(buffer_size=AUTOTUNE)
validation_data = validation_data.prefetch(buffer_size=AUTOTUNE)

# Train the model
model.fit(train_data, validation_data=validation_data, epochs=10)
```

Fig.5 Model Validating

Model Testing: The process of evaluating the trained DMN (Deep Maxout Network) model on the test dataset is performed. The test dataset consists of a collection of sugarcane billet images that the model has not seen during its training or validation phases. The goal is to assess the model's performance on previously unseen data, thereby gauging its ability to generalize to real-world scenarios.

This evaluation process is essential for validating the model's readiness for deployment in the Sugarcane Billet Damage Detection App. A high test accuracy suggests that the model is capable of accurately categorizing

```
In [5]: # Assuming you have 'test_data' directory inside your 'split' dataset directory
test_directory = './split/test'

# Create a TensorFlow Dataset object for the test data
test_data = tf.keras.preprocessing.image_dataset_from_directory(
    directory=test_directory,
    batch_size=32,  # Adjust the batch size as needed
    image_size=(224, 224),  # Adjust the image size to match your model's input size
    shuffle=False,  # Don't shuffle the test data
    seed=42,  # Random seed for reproducibility
)

# Evaluate the model on the test data
test_loss, test_accuracy = model.evaluate(test_data)
print(f"Test accuracy: {test_accuracy}")

Found 83 files belonging to 6 classes.
3/3 [==============================] - 3s 719ms/step - loss: 0.1835 - accuracy: 0.9639
Test accuracy: 0.9638554453849792
```

sugarcane billet damage, bolstering its usability for real-world applications.

Fig.6 Model Testing

- **Conversion to TensorFlow Lite (TFLite) Format**

Export Trained Model: Once training is complete, the trained DMN model is exported in a format compatible with TensorFlow Lite. This format allows for efficient execution on mobile devices.

Quantization (Optional): Depending on the hardware and memory constraints of the target Android devices, model quantization may be applied to reduce the model's size while maintaining acceptable accuracy.

Conversion to TFLite: Using TensorFlow's TFLite Converter, the trained model is converted into TensorFlow Lite format (.tflite). This lightweight format is optimized for mobile and edge devices.

```
In [15]: converter = tf.lite.TFLiteConverter.from_saved_model("sugarcane_damage_model")
         tflite_model = converter.convert()
         open("sugarcane_damage_model.tflite", "wb").write(tflite_model)

Out[15]: 44683012
```

Fig.7 Model Converting to TFLite

- **Integration with Android Studio**

Android Studio Setup: In Android Studio, a dedicated project for the Sugarcane Billet Damage Detection App is created. The necessary dependencies for TensorFlow Lite integration are configured.

Assets Folder Creation: An assets folder is created within the Android Studio project directory to store the converted TFLite model (.tflite) and any associated files required for inference.

TensorFlow Lite Interpreter: In the Android app's code, a TensorFlow Lite interpreter is initialized. The TFLite model is loaded into this interpreter, making it ready for billet damage categorization.

User Interface Integration: The Android app's user interface (UI) is designed to include a dedicated button or functionality for users to initiate the billet damage detection process. User interaction triggers the TFLite model for inference. The User interface is maintained simple for ease of use by the farmers.

Pre-processing: Prior to inference, any necessary pre-processing steps, such as image resizing, normalization, and median filtering, are implemented within the Android app using TensorFlow Lite's image processing capabilities.

Inference and Post-processing: The TFLite interpreter is utilized to run inference on user-provided images of sugarcane billets. The model's output is processed to provide users with clear and accurate damage categorization.

- **Testing and Optimization**

Testing: Extensive testing is conducted to ensure the accuracy and reliability of the integrated model within the Android app. Real-world billet images are used to assess the model's performance.

Optimization: If necessary, optimizations are made to enhance the app's performance, including improvements in inference speed, memory usage, and user experience.

- **Deployment and User Authentication**

Deployment: The Sugarcane Billet Damage Detection App, now equipped with the integrated TFLite model, is prepared for deployment on Android devices.

User Authentication: User authentication and data privacy measures are integrated into the app to ensure secure access and data protection. This authentication system is essential for user identity verification and access control.

The integration of TensorFlow Lite streamlines the deployment of the model, making the app user-friendly and efficient. This comprehensive methodology encompasses model preparation, conversion to TFLite, and seamless integration into Android Studio, ensuring the Sugarcane Billet Damage Detection App delivers accurate and actionable results to users.

RESULTS

The Sugarcane Billet Damage Detection App is designed to provide users with a seamless and informative experience. It incorporates user authentication, educational content on sugarcane cultivation, and a powerful billet damage detection system. Below are key features and user interactions within the app:

- **User Authentication**:

  The app begins with a secure login and sign-up process, ensuring user authentication and data privacy. This authentication system is seamlessly integrated into the app's framework to establish user identity and access control.

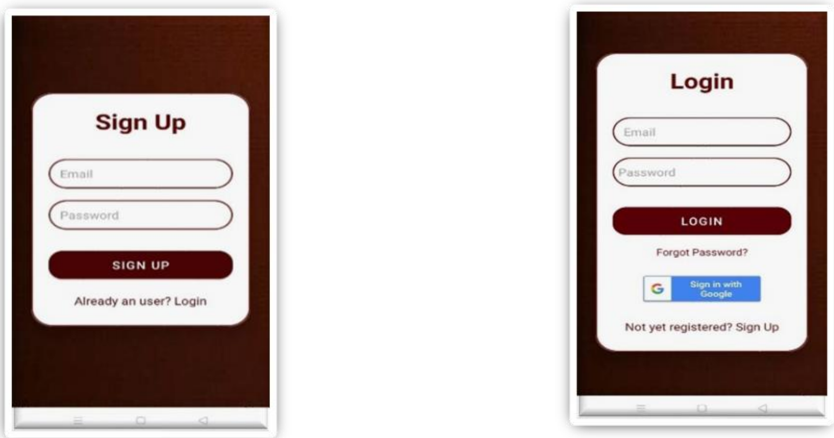

Fig.8 User Interface for User Authentication

- **Information on Sugarcane Cultivation:**

Educational Content: Upon successful login, users gain access to a dedicated section within the app that offers valuable insights into the significance of sugarcane in agriculture and provides detailed cultivation guidelines. The content within this section is dynamically loaded to ensure that users receive the most relevant and accurate information.

- **Billet Damage Detection and Results Presentation:**

Scanning Process: Users can initiate the billet damage detection process with a simple click. In this application we have two methods for input image, that are **Scan Image** and **Select from Device.** This action triggers the integration of the TensorFlow Lite (TFLite) model for damage categorization. Users are guided through the scanning process, making it intuitive and user-friendly.

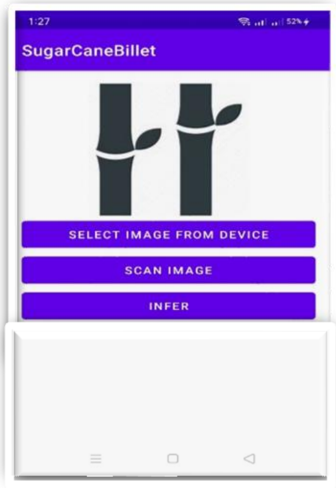

Fig.9 User Interface for Scanning Process

Results Presentation: After the scanning process, TensorFlow takes over the post-processing of results to ensure clarity and comprehensibility. Users are presented with rapid and highly accurate results regarding the condition of sugarcane billets. These results are provided in a clear and user-friendly format, enhancing the overall usability of the app.

This content section provides an overview of the app's key functionalities, emphasizing the seamless user experience, the availability of educational content, and the efficiency of billet damage detection with clear and rapid results presentation. It highlights how the app caters to both informative and practical needs, making it a valuable tool for sugarcane farmers and cultivators.

Fig.10 Result of identified six classes

CONCLUSION

The development of the Sugarcane Billet Damage Detection App represents a significant advancement in modern agriculture. This innovative app seamlessly integrates user authentication, educational content on sugarcane cultivation, and a powerful billet damage detection system, all within a user-friendly interface. Also achieved the accuracy of 96.385% result while building the model. Further the application can be developed in regional languages to help the farmers to use it more efficiently.

The key highlights and achievements of this project includes:

Deep Learning Model Integration: The integration of the Fractional Deer Hunting Optimization Algorithm-based Deep Maxout Network (FDHOA-based DMN) using TensorFlow Lite (TFLite) enables precise and efficient categorization of sugarcane billet damage. The model exhibits high accuracy, sensitivity, and specificity, making it an invaluable tool for sugarcane farmers.

***Educational Content*:** The app's educational section offers comprehensive insights into sugarcane cultivation, emphasizing its significance in agriculture. The dynamic loading of content ensures that users receive up-to-date and relevant information, promoting sustainable cultivation practices.

***User-Friendly Scanning Process*:** Users can effortlessly initiate the billet damage detection process with a single click. The intuitive interface guides users through the scanning process, ensuring accessibility for a wide range of users.

Clear and Rapid Results Presentation: TensorFlow's post-processing capabilities guarantee that users receive clear, comprehensible, and rapid results regarding the condition of sugarcane billets. This swift feedback empowers farmers to make informed decisions, enhancing crop yield and minimizing disease spread.

In summary, the Sugarcane Billet Damage Detection App not only streamlines the detection of billet damage but also serves as an educational resource for sugarcane cultivators. Its user-friendly design, accurate damage categorization, and valuable cultivation insights make it an indispensable tool in modern sugarcane farming. This project marks a significant contribution to agriculture, promoting efficiency, sustainability, and knowledge dissemination within the industry.

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