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AI-Driven Weed Classification for Improved Cotton Farming in Sindh, Pakistan

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This research study proclaims the combination of artificial intelligence and also IoT in precision agriculture, highlighting weed discovery plus cotton plant monitoring in Sindh, Pakistan. The uniqueness lies in creating a deep learning-based computer system vision application to develop a durable real-time weed category system, dealing with a problem not formerly solved. The study entailed gathering datasets utilizing mobile cams under varied ecological problems. A CNN version was educated utilizing the open-source Cotton Weeds dataset, annotated with clinical problems such as Broadleaf and Horse Purslane. Examinations used a Wireless Visual Sensor Network (WVSN) with Raspberry Pi for real-time photo catching as well as category. The CNN version, readjusted to identify in between cotton along with Horse Purslane weed accomplished a precision of 86% and also an ROC AUC rating of 0.93. Efficiency metrics consisting of precision-recall, as well as F1 rating, suggest the model's viability for various other weed category jobs. Nonetheless, obstacles such as photo top-quality variants and also equipment constraints were kept in mind. The research ends that using artificial intelligence as well as IoT in farming can dramatically improve plant return plus assist lasting methods for future generations.

Keywords: Precision Agriculture; Weed Detection; Machine Learning IoT and Cotton Weeds.

Introduction:

Agriculture has recently become an increasingly effective economic sector, contributing greatly to the global economy. The World Bank reports that the agriculture industry sustains over a billion people, which constitutes around 28.5% of the total manpower, and creates an estimated 10 million tons of food every day [1]. Despite this importance, Nevertheless, the industry still faces many challenges, one of which is the prevalence of plant infections and diseases, which can greatly impact global food security. Major crops such as rice, wheat, potatoes, soybeans, and maize can lose from 10% up to 40% of their yield due to plant viruses [2].

Conventional disease inspection methods are mostly inefficient fields. Consequently, there is a growing interest in utilizing machine learning approaches to automate disease detection mechanisms through image analysis [3]. Researchers have been extracting critical features from field images to enable machine learning–based classification of diseases. Some researchers utilized the SVM algorithm along with SIFT feature extraction, which showed excellent performance in classifying diseases in guava leaves. Significantly innovations in computer technology, coupled with artificial intelligence algorithms, have impacted precision technology. Modern computers' processing power and the development of novel artificial intelligence algorithms have led to substantial progress in this field, including the introduction of robotic weed differentiation mechanisms, which have revolutionized weed management. In this era of modern technology, the visual sensors incorporated within robotic platforms are assisting the production of site-specific treatments, allowing better and more sustainable operation of agriculture [4]. Weeds pose a significant threat to agricultural yields consuming about 90% of sunlight, water, and fertilizers. The agriculture sector in Pakistan still relies on traditional hand weeding and associated costs of labor. However, robotics allow affordable technology that can leverage the use of vision-based sensors interface with agriculture. Specifically, the application of computer vision coupled with machine learning algorithms can differentiate between the weed and crop; hence the application of a site-specific crop planning mechanism is possible [5].

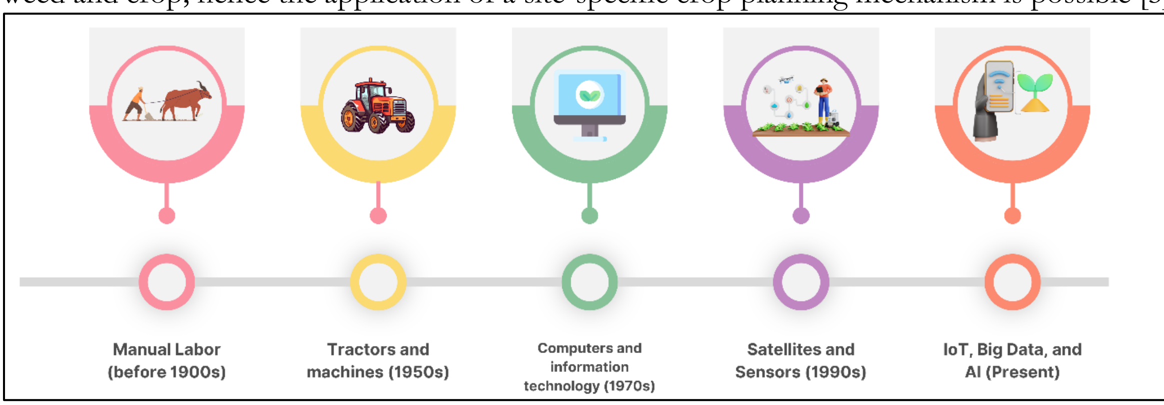

Figure 1. From Manual Labor to AI: A Timeline of Agricultural Advancements

This research aims to build an accurate weed classification system, focusing on the real-time application of weed detection within the cotton fields. In Sindh, Pakistan's agricultural landscape, the urgency to embrace Machine Learning parallels the advancements observed in international agricultural methodologies. It is, therefore, important to develop a complex system that can examine agricultural factors carefully for effective crop management. By integrating Artificial Intelligence (AI) and Internet of Things (IoT) technologies, Sindh's agriculture industry could experience a significant increase in its productivity thereby turning it into an international agriculture hub in Pakistan [6]. The overall goal is to have a flexible decision support framework for high-yielding crops developing a strong Sindh foothold in Pakistan's agricultural revival. Technological improvements from human labor to artificial intelligence automation have significantly boosted agriculture production, and increased efficiency as well as food security. As technologies develop further, the agri-food revolution is likely to accelerate. Promisingly, the technology could eventually be applied at larger scales to help in the effort to tackle more global challenges — such as climate change, resource scarcity, and population growth as shown in Figure 1.

Cotton crops in Sindh, Pakistan face significant challenges from various weeds including Amaranthus viridis L. (Slender Amaranth), Convolvulus arvensis L. (Field Bindweed), Cyperus rotundus L. (Nutgrass or Purple Nutsedge), and notably, Trianthema portulacastrum L. (Horse Purslane) [7]. These invasive species compete with cotton plants for essential nutrients, -water, and space thereby diminishing crop yields and impeding agricultural productivity.

Objectives:

The proposed research study presents an ingenious assimilation of artificial intelligence plus computer system vision methods right into the world of low-priced farming methods especially targeting the spread of Horse Purslane in cotton fields. The novelty of this approach lies in the smooth mix of a Wireless Visual Sensor Network (WVSN) with advanced machine learning classifiers, which enables real-time precise distinction between cotton plants along Horse Purslane. This system is made to be economical and also obtainable taking advantage of Raspberry Pi to record as well as transmit leaf images for remote processing. By offering farmers prompt positive understandings with a mobile application this research not only improves weed management but also promotes sustainable agricultural practices.

To combat this issue effectively, our primary focus lies on tackling the proliferation of Horse Purslane. Our proposed solution entails the development of a machine learning model adept at accurately distinguishing between cotton plants and the targeted invasive weed, Horse Purslane. Furthermore, using state-of-the-art computer vision methods and machine learning models, we aim to create a strong mechanism for the live detection and classification of weeds in the cotton fields. This approach provides farmers with timely enabling them to implement effective control measures, improve their cultivation methods, and increase their production while promoting sustainability. This study aims to introduce automation and technology into low-cost farming practices. A Wireless Visual Sensor Network (WVSN) using Raspberry Pi serves as the backbone of this system which is capable of capturing leaf images and transmitting them to a base station [8]. The base station, in turn, forwards the images to a remote station (cloud) for processing. A Classifier extracts features from these images to identify weeds within the crop. The resulting data is capable of informing appropriate decisions, communicated to farmers via a mobile application.

Literature Review:

In recent years, various approaches have been studied, ranging from traditional artificial neural networks, support vector machines (SVM), random forests, and k-nearest neighbors (KNN) to innovative methods based on deep learning [9]. In particular, significant attention is paid to machine learning algorithms-based RF, SVM, and KNN applied to weed detection based on images from unmanned aerial vehicles [10]. These studies aimed to demonstrate the effectiveness and high performance of such machine learning algorithms that can be adopted in agricultural science and technology during weed detection operations. In addition to ML, recent innovative solutions include image processing to distinguish plants from weeds, which speeds up the recognition processes of the new tools and achieves high performance and accurate results in different working environments [11]

Transformer-based models have also been revamped to improve weed-detection performance. The first strategy involves hybridizing the model, combining a Convolutional Neural Network and the Transformer architecture, aiding the extraction of intermediate feature maps [12]. The second strategy, however, lessens the intricacy of the self-attention mechanism in pure Transformer models. While the Transformer-based model has shown progress, challenges remain in implementing the model in resource-poor environments. Nevertheless, active measures to reduce model complexity and resource utilization ensure effective implementation in intelligent edge applications, enhancing applicability in agricultural domains [13].

The utilization of machine learning and image processing in weed detection has demonstrated immense potential to enhance the functionality and viability of various applications in agriculture and other sectors. Consequently, it is noted that the development and other revolutions are not limited to agricultural technologies but can shape the entirety of agricultural practices to promote sustainable agriculture. The development of precision agriculture is facilitated by modern technologies such as machine learning and image processing. Through the integration of computing and data analytical tools to wireless sensor network technologies, decisions have been made about several agricultural features, such as favorable weather conditions, and the management of crop and livestock-related problems, including the best irrigation practices that will enhance reliable decisions. The target of all these technologies is to give a farmer the best advice regarding the growth stages of the crop to increase the crop yield and eventually the revenue.

While many promising results have been achieved in the healthcare sector [14], their potential for substantial convenience and enhanced operations in the agriculture sphere is evident as well. Addressing farmland monitoring and management, an excellent tailored solution to tackle the issue is WSN architectures based on the type of node movement. Given that the economy of India is significantly reliant on the agriculture sector, where known challenges include low production levels and farmer issues, the development of the proposed systems is essential. These are the embedded systems for soil monitoring and irrigation, including the microcontroller, designed to collect data and analyze it to support decisions on selection of suitable crops for plantation during certain time [15].

In addition, intelligent scheduling and networked farming are revolutionizing the agricultural sector, providing precise crop control and automated agriculture solutions. Smart farming proposals can aid in pooling resources to address issues including water shortage, scarcity restriction, and high operating costs, all of which have expanded through the Internet of Things (IoT). With the aid of IoT devices, spanning from sensors to intelligent tools, farmers can monitor and control agricultural processes in real-time with considerable power efficiency and benefit across resource management [16]. The IoT ecosystem incorporates variable and connected units from modest capturing units to big smartphones is a massive correlated network that combines actual-time monitoring of agricultural produce logistics and control in real time.

Finally, technologies such as the ESP8266 combined with devices such as Arduino and Raspberry Pi ensure that all the described processes can be miniaturized and energy-efficient. These compelling innovations guarantee that communication is maintained easily and that access to sensor data takes it to the next level while ensuring sustainable agriculture practices [17]. Moreover, by combining the processes with other technologies, such as LoRaWan for long-distance and solar-powered IoT devices for energy efficiency, the agricultural industry may adjust precision farming and resource management to novel levels [18]. The combinations of hardware, sensing technology, optimal communication systems, and coordinated computer applications, therefore, have a very promising result. The continued advancement in machine learning, image processing, and IoT technologies provide exciting solutions to challenges faced by the agricultural sector, and hence they will significantly contribute to the improvement of rate and yield in agricultural settings globally.

Methodology:

The methodology of the experimental setup integrates hardware and software components designed to enhance image classification efficiency. The hardware includes a Raspberry Pi, and HD webcam as a visual sensor for area coverage. Raspberry Pi is a single-board computer that works in many areas of engineering, such as image processing, control systems, and data flow. Raspberry Pi is utilized to capture images and analyze them in the case of image processing. The GPIO pins and camera module allow it to be interfaced with HD cameras [19]. In addition, it is also employed for acquiring data, processing, and transmitting them to cloud storage. It therefore acts as an IoT system that detects weeds in real time. Bluetooth ensures real-time communication and synchronization between devices.

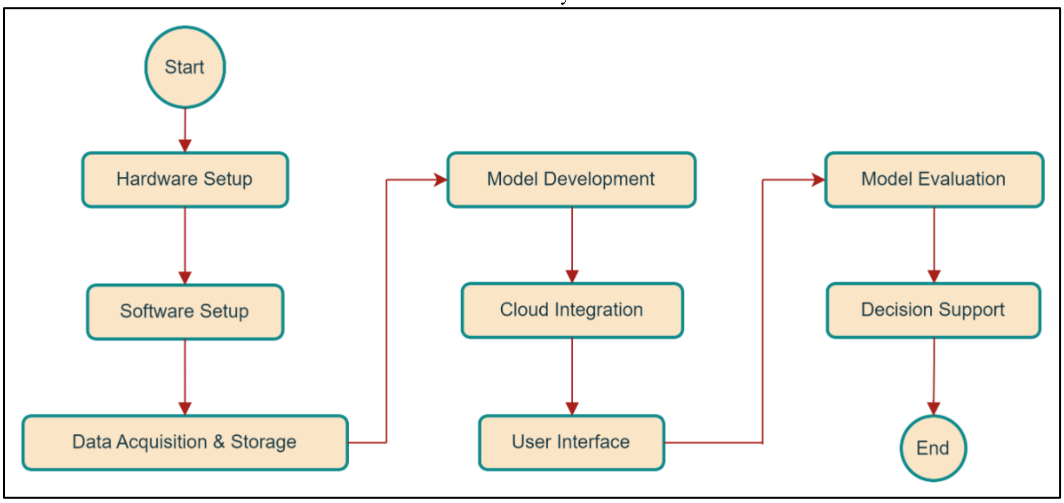

Figure 2. Flow of methodology

The software part used a Cotton Weeds dataset [20], with Python 3.10 as the primary programming language due to its adaptability and extensive libraries. Another tool, OpenCV, is widely used for image manipulation and preprocessing, including feature extraction. The deep learning task was performed with the help of Keras with a TensorFlow backend. The software components helped develop an image classifier that would differentiate the images of cotton plants. Moreover, integration with Google Cloud APIs allows for easy access to other cloud-based services like storage, data analytics, and deployment of machine learning models. In addition, Google Colab was utilized as a collaborative platform to develop and test algorithms, which provided an easy option for rapid prototyping. The implementation of our model has also used the transfer learning concept employing pre-trained models such as Mobile Net [21]. According to these models, learning can continue seamlessly from where it left off, drawing on the vast volumes of knowledge mined from large datasets. This allows the model to quickly grasp new concepts and reinforce them with each iteration [22][23]. Firebase was utilized, with Google Fire store database to ensure proper management of data and save large data sets and at the same time access the data after its deployment. Lastly, the user interface is embedded in Flutter. This was important to get an ideal intuitive interface and improve user experience.

A CNN model was trained using the Cotton Weeds dataset by capturing images through mobile cameras across districts within Pakistan [24]. This dataset which contains annotated images of cotton, horse purslane, and purple nutsedge was compiled to facilitate weed classification in cotton fields. For precise classification purposes, the images were resized to 640 × 480 and labeled with bounding box coordinates. The Convolutional Neural Network (CNN) has emerged as a prevalent choice for image classification tasks due to its capability to extract features from images through the application of filters. Unlike traditional machine learning models, CNNs alleviate the need for manual feature selection, which typically necessitates domain expertise [25]. However, CNNs often encounter the challenge of overfitting, wherein the model performs well on the training data but poorly on unseen test data, especially when trained on limited data. To address this issue, transfer learning offers a solution by leveraging pre-trained models developed for one task and adapting them for another task without starting the training process from scratch. This approach has shown promise, particularly when dealing with smaller datasets. For our study, we opted to employ Mobile Net, a lightweight CNN model widely utilized in mobile applications, for the transfer learning framework.

The experimental setup strongly focuses on experimentation and iteration, allowing for refined and optimized iterations based on empirical evaluation results. In summary, the matching methodology follows a complete and systematic procedure for the development and assessment of the experimental setup proposed for image classification. Moreover, the mobility of mobile cameras enabled the acquisition of images from diverse angles, ensuring the capture of multiple features essential for our Machine Learning model. Approximately 300 images were amassed for both Cotton and Weed classes. Samples showcasing representatives from each class, namely cotton and weed, are depicted in Figures 3 and 4, respectively.

Figure 3. An image of Cotton Plant

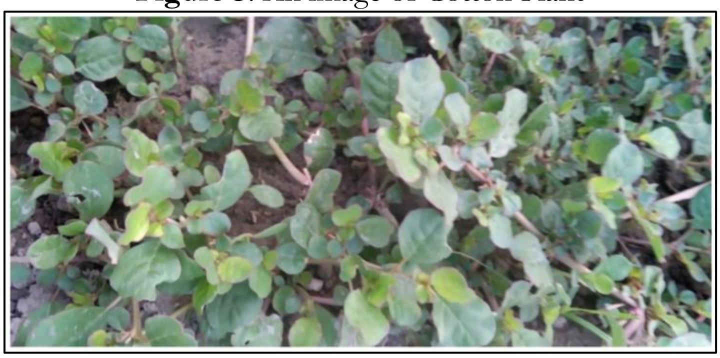

Figure 4. Weed withing Cotton Crop (Horse Purslane)

Code Explanation:

We describe the main processes involved in data preparation, model creation, compilation, training, and evaluation to give a thorough knowledge of our code. To help with clarity and reproducibility, each step is described in depth with a matching pseudocode. This explanation seeks to lead readers through our suggested fix by emphasizing the vital elements and procedures that support the model's functionality.

To train and evaluate our image classification model, we utilized the `Image DataGenerator` class from Keras to scale pixel values and generate batches of image data with real-time data augmentation. The training and testing datasets were loaded using the `flow_from_directory` method, specifying a target image size of 200x200 pixels and a batch size of 64.

Algorithm 1: Data Preparation

Function initialize_data_generators():

datagen = ImageDataGenerator(rescale=1.0/255.0)

train_it = datagen.flow_from_directory('dataset/train/', class_mode='binary', batch_size=64, target_size=(200, 200))

test_it = datagen.flow_from_directory('dataset/test/', class_mode='binary', batch_size=64, target_size=(200, 200))

Return train_it, test_it

Model Definition:

We designed a Convolutional Neural Network (CNN) model using Keras' Sequential API. The model consists of three convolutional layers with ReLU activation and 'he uniform' kernel initializer, each followed by max-pooling layers. The final layers include a flattened layer and two Dense layers, the last with a sigmoid activation function for binary classification.

Algorithm 2: Model Definition

```
Function define_model():
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same', input_shape=(200, 200, 3)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu', kernel_initializer='he_uniform'))
model.add(Dense(1, activation='sigmoid'))
Return model
```

Model Compilation:

The model was compiled using the Stochastic Gradient Descent (SGD) optimizer with a learning rate of 0.001 and a momentum of 0.9. The loss function used was binary cross-entropy, and the performance metric was accuracy.

Algorithm 3: Model Compilation

```
Function compile_model(model):
opt = SGD (learning_rate=0.001, momentum=0.9)
model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
Return model
```

Model Training

The model was trained using the training dataset with validation on the testing dataset for 20 epochs.

Algorithm 4: Model Training

```
Function train_model(model, train_it, test_it):
history = model.fit(train_it, steps_per_epoch=len(train_it), validation_data=test_it, validation_steps=len(test_it), epochs=20, verbose=0)
Return History
```

Model Evaluation: After training, the model's performance was evaluated on the test data. Predictions were made and converted from probabilities to class labels. The classification report, including precision, recall, and F1-score for both classes (Weed and Cotton), was generated to assess the model's accuracy.

Algorithm 5: Model Evaluation

```
Function evaluate_model(model, test_it):
yhat_probs = model.predict(test_it, verbose=0)
yhat_classes = (yhat_probs > 0.5).astype("int32")
yhat_classes = yhat_classes[:, 0]
report = classification_report(test_it.classes, yhat_classes, target_names=['Weed', 'Cotton'])
Print(report)
Return report
```

The complete Python code is publicly available at [26]

Results:

To evaluate the model's performance with precision, we conducted a thorough 10-fold cross-validation approach, assessing the model's efficiency across various segments of the training data. This meticulous process yielded an impressive accuracy rate of approximately 86%, demonstrating the model's effectiveness in making accurate predictions. Nonetheless, our assessment extended beyond plain precision dimensions. We explored intricate details of model performance by incorporating the ROC AUC statistics, a vital device in category evaluation. ROC AUC, or Receiver Operating Characteristic Area Under the Curve, offers a nuanced perspective on the model's classification abilities [27]. A ROC AUC worth coming close to 1 underscores the model's adroitness at identifying in between various courses, bolstering its dependability in real-world category circumstances. By using a diverse examination strategy including precision as well as ROC AUC we made certain an extensive evaluation of the version's anticipating efficiency along with prejudiced power. The bar chart shown in Figure 5 compares two efficiency metrics. The ROC AUC (Receiver Operating Characteristic Area Under the Curve) statistics is commonly used in binary category circumstances to scale a model's capability to identify between favorable and also unfavorable courses.

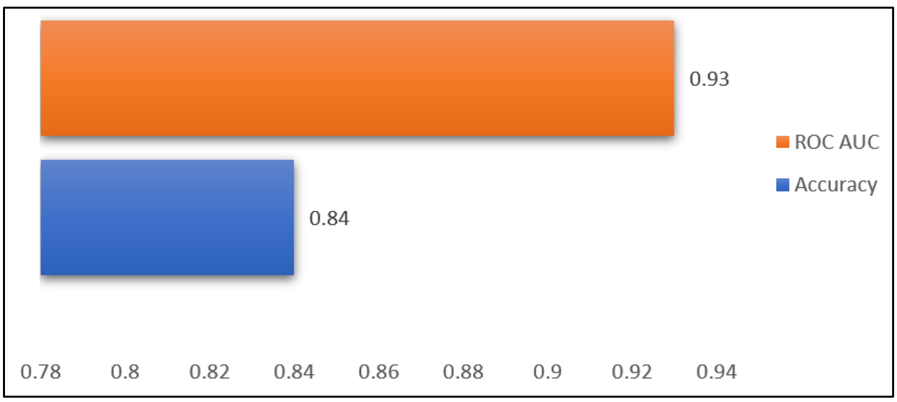

Figure 5. The bar graph illustrates a comparison of two performance metrics

Precision, on the other hand, determines the percentage of right forecasts made by the proposed model. With a precision rating of 0.84, the model properly anticipates results in about 84% of instances. While this provides a general overview of the model's performance in terms of overall accuracy, it may not be sufficient for imbalanced datasets or situations where misclassification rates vary across classes. The combined evaluation of both ROC AUC and precision highlights the model's strong performance and reliability in its classification. Nonetheless, it's vital to acknowledge that depending entirely on these two metrics could not supply a detailed analysis. Additional metrics such as recall, along with the F1 score and domain-specific considerations, are necessary for a full understanding of the model's performance, especially in complex or nuanced classification tasks.

The efficiency metrics for private courses, concentrating on the accuracy, recall, as well as F1 rating offer beneficial understandings right into the model's performance in distinguishing between Cotton and Weed circumstances as revealed in Figure 6 [28]. Precision, which measures the accuracy of the model's positive predictions, shows that for weeds, the precision is 0.90, indicating a 90% accuracy rate in identifying weeds. For cotton, the precision stands at 0.82, representing an 82% accuracy rate in cotton recognition.

Recall, analyzing the model's capacity to discover all appropriate circumstances. For weeds, the model has a recall of 0.64, correctly identifying 64% of all actual weed instances. On the other hand, for cotton, the recall is greater at 0.96 showing a 96% success price in locating all cotton circumstances existing in the information collection.

F1 Score, which provides a well-balanced step of accuracy plus recall, supplies additional understanding. With an F1 rating of 0.75 for weeds and 0.88 for cotton, the model accomplishes satisfying equilibrium and precision in identifying both courses. This suggests that while the model is more precise in identifying weeds, it excels in recalling (finding all instances of) cotton within the dataset. These metrics show that the version generally shows exceptional efficiency in categorizing cotton contrasted to weeds. The greater accuracy, recall, and F1 rating for cotton suggest that the version's forecasts for this course are much more exact and trustworthy. However, the lower recall score for weeds suggests that the model may struggle to identify all weed instances accurately, leading to potential misclassifications. This extensive evaluation uses beneficial understandings right into the model's toughness along with weak points preparing the method for possible renovations as well as optimizations in future models.

Figure 6. Model Performance for Identifying Weeds and Cotton

Discussion:

We have carefully assessed the performance of our model and gained useful insights about its efficiency in classification tasks. The model gives an 86% general accuracy in predicting diverse segments of the training data. In this regard, precision is also a critical tool for assessing positive results accuracy as it's about 84%. This shows how well our model can predict future events. Apart from considering only the accuracy and precision measures, the ROC AUC statistics are employed to measure into depths of the performance of models. Our model has a large ROC AUC value (0.93), meaning it has excellent discrimination ability because it has a high true positive rate and low false positive rate when distinguishing various classes. Consequently, this subtle perspective provides some remarkable insights into its classifier abilities while confirming that if applied in real-world situations, it is still reliable. Also, our analysis goes beyond looking at overall performance indicators to examine how well the model performs concerning each category i.e. weeds and cotton separately. While weed's class can be precisely predicted by the model with an accuracy of 90%, that for cotton is 82%. Despite having the same precision rate of 90% and 82% for weeds and cotton respectively, the recall figures are different. This is shown by the fact that while it can accurately detect true positive cases of both classes, there may be a problem in identifying all positive weeds' instances correctly. his is made clearer by the F1 score, which balances precision against recall. Our model has a .75 F1 score for weeds and a 0.88 F1 score for cotton thus striking reasonable tradeoffs between both accuracy as well as recall on these two classes thereby revealing its overall performance in classification tasks. However, our evaluation of it while at the same time commending it, recognizes some areas where improvement can be affected. The low recall value for weeds shows that this model is wanting since some instances belonging to that group might not be predicted leading to misclassification of them as other things. Nevertheless, despite these strengths, several weaknesses have been identified through this review process. This comprehensive breakdown covers all aspects of our current modeling technique but also provides us with suggestions on how to improve upon it making it more efficient and reliable when applied in practice.

Conclusion:

In conclusion, combining state-of-the-art innovations like artificial intelligence (AI), and computer vision systems along with the Internet of Things (IoT) has shown great promise in revolutionizing precision farming, particularly in regions like Sindh, Pakistan. With the precise expedition of techniques, literary works along functional applications, this research study has highlighted the importance of automated weed discovery together with category systems in boosting farming performance coupled with sustainability. By leveraging artificial intelligence formulas coupled with photo handling methods, paired with the release of cordless sensing unit networks plus shadow computer facilities, we have shown the expediency of real-time weed category in cotton areas. Our technique, which entails the build-up of area pictures, training of semantic network models, together with smooth assimilation with mobile applications for choice assistance provides a detailed service to attend to the consistent obstacle of weed invasion. The examination of our model's efficiency, as shown by precision, ROC AUC, accuracy, recall as well as F1 rating metrics, highlights its efficiency in comparing cotton plants plus intrusive weed types significantly Horse Purslane. Though the results suggest good performances in detecting cotton scenarios, there is also room for improvement. These include ways to increase the recall rate of the model for weed scenarios as well as methods to address some of the constraints like image quality discrepancy and limitations of the hardware used. This research study significantly concentrates on leveraging innovative innovations such as artificial intelligence, computer system vision plus IoT to attend to weed invasion obstacles in farming setups, particularly in Sindh, Pakistan. The recommended approach entails the growth of a real-time weed category system utilizing cordless sensing unit networks together with a shadow computer framework. By accumulating area photos, educating deep convolutional semantic network models, as well as incorporating mobile applications for choice assistance the research shows the usefulness of automated weed discovery in cotton areas. These consist of irregularity in picture top quality from mobile cams restrictions in transfer learning adaptability, source constraints in equipment arrangements like Raspberry Pi, difficulties in WSN release as well as the requirement for dressmaker came close to for various plant kinds as well as governing conformity with information security. Dealing with these restrictions needs interdisciplinary cooperation as well as cutting-edge remedies. Future models ought to concentrate on fine-tuning information collection approaches, boosting model versatility, enhancing equipment executions along making certain conformity with information personal privacy policies. By overcoming these difficulties, the research intends to add to lasting farming techniques coupled with financial development in farming areas like Sindh, Pakistan.

In conclusion, the limitations described provide directions for future work. An important aspect is to minimize the bias described above and thus future work should focus on measures to improve it. A key area that needs to be improved is data acquisition techniques to reduce image quality disparity.

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Author's Contribution: Dr. Abdul Aziz Conceptualized the research study created the method as well as gathered the dataset utilizing mobile cams in varied ecological problems.

- Engr. Ali Raza Created and trained the CNN version utilizing the CottonWeeds dataset as well as executed the experiments with the Wireless Visual Sensor Network (WVSN) utilizing Raspberry Pi for real-time photo catching and also category.
- Engr. Muhammad Irfan Younas Analyzed the efficiency metrics consisting of accuracy recall, and F1 rating, as well as evaluated the model's precision plus ROC AUC rating.

- Dr. Abdul Sattar Chan Contributed to the analysis of the outcomes and went over the restrictions such as picture top quality variants as well as equipment source restraints as well as supplied understandings for the wrapping up comments.

Conflict of Interest: There exists no conflict of interest for publishing this manuscript in IJIST.

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