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Jute Pest Identification using Deep Learning Algorithms

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ABSTRACT- Jute is a crucial cash crop cultivated extensively across countries like Bangladesh, India, and China, faces significant threats from various pests, posing substantial risks to crop yield and quality. To address this challenge, a deep learning model has been developed in this project specifically for Jute Pest detection and classification. The objective of the proposed system is to accurately identify different types of pests that commonly attack jute crops, leveraging a comprehensive dataset. Through rigorous training and testing on a dataset comprising images of jute pests, the EfficientNet model achieved an impressive accuracy rate of 99%. These results underscore the efficacy of the proposed system in effectively classifying different types of pests affecting jute crops. By providing timely and accurate pest identification, the system equips farmers with valuable insights to initiate prompt actions for pest control measures. Such proactive interventions can significantly mitigate the impact of pest infestations on jute crops, thereby enhancing overall yield and quality. Ultimately, the successful deployment of this system holds promise in empowering farmers with a powerful tool to safeguard their jute crops and sustainably improve agricultural productivity in regions reliant on jute cultivation

KEYWORDS: Energy efficient algorithm; Jute, Machine learning, CNN, Agriculture, Gradient Boosting

I. INTRODUCTION

Jute, often regarded as one of India's foremost natural fiber crops alongside cotton, holds significant economic importance in the country's agricultural landscape. Traditionally known as "raw jute," it shares similarities in usage and trade with mesta crops, collectively contributing to the country's economy. Initially recognized primarily for its role as a raw material in packaging industries, raw jute has evolved into a versatile resource for various sectors, including textiles, paper production, construction, automotive, soil enrichment, cosmetics, and furnishings. Its biodegradable nature and renewable annual growth make it an environmentally friendly choice, contributing to soil conservation and ecological balance.

Characterized by its distinct silky cluster, exceptional tensile strength, low extensibility, significant heat resistance, and long staple length, raw jute possesses qualities unmatched by synthetic fibers. Furthermore, its compatibility for blending with other natural and synthetic fibers enhances its versatility and applicability across industries. While mesta cultivation is widespread throughout India, jute cultivation predominantly thrives in the eastern and northern regions.Despite its importance, jute cultivation faces challenges, particularly concerning pest management. Identifying jute pests within the filaments presents a significant challenge for farmers, potentially impacting crop yield and quality. To address this issue, there is a growing demand for advanced technologies to aid in the detection and classification of jute pests. In response to this need, the development of a deep learning model becomes imperative. By leveraging the capabilities of artificial intelligence and machine learning, such a model holds promise in accurately detecting and categorizing various types of jute pests. Ultimately, the implementation of such technology could empower farmers with timely and precise pest management solutions, thereby safeguarding jute crops and ensuring sustained agricultural productivity in key regions of jute cultivation.

Agriculture is the backbone of all traditional countries [3]. One of the main aspects of human survival is the agriculture which is the main source of food [2]. It uses 85% of available fresh water resources global and this percentage continues to be leading in water consumption because of population growth and enlarged food demand an automated irrigation system is needed to adjust water level for agricultural crops. The need of automated irrigation system is to overcome irrigation and under irrigation [3]. The system was studied and developed to build the wireless sensor

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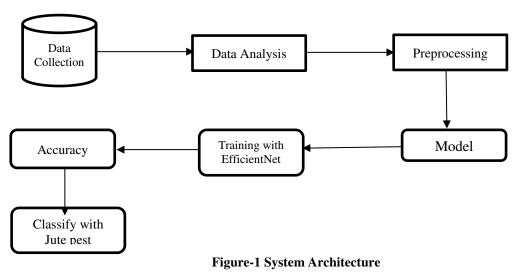
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network to assess the temperature, humidity and water level adjustment, and of the sensor node necessary for the best farming environment, and of the monitoring managing devices to collect and analyse such collected data from sensor node and to store them in the management server and to alert emergency [4]. By using the data from the sensor network, watering is automated. It saves 53% of water than sprinkler system and more than 80% of water when compared to traditional water fed system. Using the grouping of humidity, moisture, and light sensors, crop productivity can be increased [5]. The data logger on weather Station collects the data from sensors and transmits. Each farmer, seeking the service, is initially required to perform registration by providing the details of the field location, crop, crop type, soil type, and history of irrigation, fertilizer on the field [6]. Regulating all these operations will be through any remote smart device or computer connected to Internet and the operations will be performed by interfacing sensors, Wi-Fi and micro-controller and Arduino Uno [1].

II. RELATED WORK

Sabyasachi Mukherjee et al [2]., used UCI Machine Learning approach with 270 patients having heart disease with attributes of patients diagnosed reports. They identified the risk factors which influence the diagnosis using two classification techniques namely Support Vector Machines (SVM), Multi-Layer PerceptronEnsembles (MLPE) and one advanced regression technique, Generalized additive model (GAM) with binomial distribution and logit link have been introduced for diagnosis and risk factors/variables identification. The article attempted to remove some information regarding heart disease through probabilistic modeling which may provide better assistance for treatment. Swaminathan [3] used Naive Bayes, linear regression and k-means algorithm for data analysis and prediction in the data sets of diabetic children. The model predicted the diabetes affected children with maximum level of accuracy 96% by using the said algorithms. Rajalakshmi et al [4]., used K-Means, Weighted Associative Classifier (WAC) and Prediction Tree C5.0 for analysing the heart disease. The combined technology of K-Means, WAC and Prediction Tree C5.0 provided a better, integrated, and accurate result over the heart disease prediction. Theresa Princy et al [5], survived about different classification techniques used for predicting the risk level of person based on age, gender, blood pressure, cholesterol, pulse rate. The patient risk level is classified using data mining classification techniques such as Naïve Bayes, KNN, Decision Tree Algorithm, Neural Network. etc. The accuracy of risk level is high when using more number of attribute is employed. Patil., [6] proposed an efficient approach for the extraction of significant patterns from the heart disease warehouses for heart attack prediction. The heart disease warehouse is clustered using the K-means clustering algorithm and MAFIA algorithm which will extract the data relevant to heart attack from the warehouse. Theprediction system found out the significant patterns in the development of heart attack. ParasPrafulChavda et al., [7] used a machine learning algorithm on cardiac-related data and attempted to detect the possibility of cardiac diseases prior to suffering from serious issues. Implementation showed the effectiveness of the approach in early prediction of cardiac diseases. ShreshthTuli et al., [8] developed a framework called HealthFog for integrating ensemble deep learning in Edge computing devices and deployed it for a real-life application of automatic HeartDisease analysis. HealthFog delivers healthcare as a fog service using IoT devices and efficiently manages the data of heart patients, which comes as user requests. HealthFog is configurable to various operation modes which provide the best Quality of Service or prediction accuracy, as required, in diverse fog computation scenarios and for different user requirement



III. PROPOSED ALGORITHM

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Algorithm Step 1: Read the image Step 2: Convert into RGB to HSV Step 3: Set Image h = hsv(:,1); s = hsv(:,2); v = hsv(:,3); Step 4: Finds location of black and white pixels Step 5: Gets the number of all pixels for each color bin Step 6: To find the number of pixels Step 7: Plots histogram

Color image segmentation that is based on the color feature of image pixels assumes that homogeneous colors in the image correspond to separate clusters and hence meaningful objects in the image [1]. Each cluster defines a class of pixels that share similar color properties. In this work, a segmentation of color images is tested with RGB and HSV color spaces. The HSV color space gives the best result compare to other color spaces. The median filter is used to remove the noise from the images. This filter is used to calculate the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle pixel value.

IV. SIMULATION RESULTS

import pand	las as pd
import nump	yy as np
import os	
os.environ	<pre>('TF_CPP_MIN_LOG_LEVEL'] = '2'</pre>
import time	
import matp	olotlib.pyplot as plt
import cv2	
import seab	orn as sns
sns.set_sty	<pre>/le('darkgrid')</pre>
import shut	il
from sklear	n.metrics import confusion_matrix, classification_report
from sklear	n.model_selection import train_test_split
import tens	orflow as tf
from tensor	flow import keras
from tensor	flow.keras.preprocessing.image import ImageDataGenerator
from tensor	flow.keras.layers import Dense, Activation, Dropout, Conv2D, MaxPooling2D, BatchNormalization
from tensor	flow.keras.optimizers import Adam, Adamax
from tensor	flow.keras.metrics import categorical_crossentropy
from tensor	flow.keras import regularizers
from tensor	flow.keras.models import Model
from tensor	flow.keras import backend as K
import time	
from tqdm i	mport tqdm
from sklear	n.metrics import f1_score
import sys	
if not sys.	warnoptions:
import	warnings
warning	s.simplefilter("ignore")
pd.set_opti	ion('display.max_columns', None) # or 1000
pd.set_opti	<pre>ion('display.max_rows', None) # or 1000</pre>
nd.set opti	Lon('display.max colwidth', None) # or 199

Fig-2 Import Necessary packages

Found 792 validated	I image filenames belongin	ng to 4 classes. for train generator				
	Fig-3 Loa	d Image Dataset				
train_df length: 792 test_df length: 88 valid_df length: 120 average image height= 256 average image width= 256 aspect ratio h/w= 1.0						
the maximum files in any class in train_df is 198 the minimum files in any class in train_df is 198						
Value feiluw file (00.00.00.00, 30.45.211165/3) number of classes in processed datast= 4						
valid -Yellow Mite	: 100%	30/30 [00:00<00; 30349.52files/s]				
valid -Spilosoma Obligua	: 100%	30/30 [00:00 , ?files/s]</th				
valid -Jute Stem Weevil	: 100%	30/30 [00:00 , ?files/s]</th				
valid -Field Cricket	: 100%	220/220 [00:00<00:00, 218349.95files/s] 30/30 [00:00 , ?files/s]</th				
train -Spilosoma Obliqua train -Yellow Mite	: 100%	220/220 [00:00<00:00, 229824.88files/s]				
train -Jute Stem Weevil	: 100%	220/220 [00:00<00:00, 216912.76files/s]				
train -Field Cricket	: 100%	220/220 [00:00<00:00, 222134.54files/s]				

Found 792 validated image filenames belonging to 4 classes.	for train generator
Found 120 validated image filenames belonging to 4 classes.	for valid generator
Found 88 validated image filenames belonging to 4 classes.	for test generator
test batch size: 44 test steps: 2 number of classes : 4	

Fig-4 Split Dataset Train, valid and test

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learning rate will be automatically adjusted during training
Epoch 1/10 27/27 [] - ETA: 0s - loss: 7.9856 - accuracy: 0.8384 validation loss of 8.0699 is 0.0000 % below lowest loss, saving weights from epoch 1 as best weights
27/27 [====================================
27/27 [=========================] - ETA: 0s - loss: 6.7899 - accuracy: 0.9760
validation loss of 6.6556 is 17.5260 % below lowest loss, saving weights from epoch 2 as best weights
27/27 [====================================
27/27 [====================================
validation loss of 5.7973 is 12.8962 % below lowest loss, saving weights from epoch 3 as best weights
27/27 [====================================
27/27 [=========================] - ETA: 0s - loss: 5.3017 - accuracy: 0.9949
validation loss of 5.1100 is 11.8543 % below lowest loss, saving weights from epoch 4 as best weights
loading model with weights from epoch 10
training elapsed time was 0.0 hours, 53.0 minutes, 13.79 seconds)
Output is truncated. View as a <u>scrollable element</u> or open in a <u>text editor</u> . Adjust cell output <u>settings</u>

Fig-6 Model Training Process

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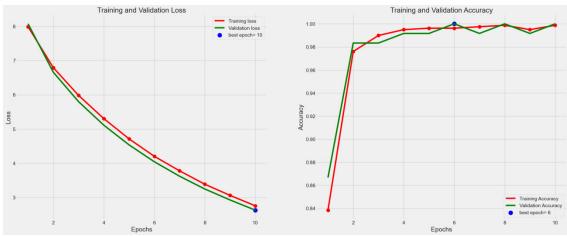


Fig-7 Loss and Accuracy Chart

V. CONCLUSION AND FUTURE WORK

In conclusion, the development of a deep learning model for jute pest identification presents a significant advancement in agricultural technology, offering farmers a powerful tool to combat pest infestations effectively. Through the utilization of the EfficientNet architecture, this project has demonstrated impressive accuracy rates in detecting and classifying various types of jute pests, surpassing the limitations of conventional methods. By providing timely and accurate pest identification, the proposed system equips farmers with valuable insights to initiate prompt actions for pest control measures, thereby safeguarding jute crops and enhancing overall agricultural productivity.

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