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The Agriculture AI Revolution: Federated Learning CNN for Jute Leaf Diseases Health

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Abstract- The present research paper discusses the novel approach of using Federated Learning FL and Convolutional Neural Networks CNN to identify and categorize jute leaf diseases at four levels of severity. Such research is primarily focused on the interpretation and transcription of local data into a unified global model based on analytical results rooted in four clients' information. Federated Learning will utilize its advanced methodologies in the research, which aims to gain a full understanding of jute leaf diseases so that appropriate measures can be taken for successful agricultural management and intervention. In this research, we applied the datasets of local clients, such as wx_1 through wx2 to 4, for analysis on precipitation rate, support in facet, and class accuracy from four classes of jute leaf disease severity. The outcomes were deeply rooted, as each of the clients indicated divergent performance levels. For instance, the average overall accuracy for client wx_1 was 91%; in addition to this, it showed the following precision recall and F scores calculated at their means equal to 82.66%: when speaking about client wx Also, clients wx_3 and wx-4 performed very well, as the first one had 92 percent overall accuracy. The crux of the study is depicted by the Federated Averaging process, where local data findings are aggregated into a global model. This was qualitatively assessed through macro, micro, and weighted averages, which are indicators of the model's performance in different datasets. Client's wx_1, wx-4 show a macro average of 82.70%. Weighted Averages were almost similar at 82.57%, In terms of the model's overall reflection, given by micro averages, these figures were found: 82.54%.

Keywords: *Jute leaves, CNN, Distributed learning, Diseases bifurcations, Severity Analysis.*

I. INTRODUCTION

In the world of agronomic developments, growing jute, a very important cash crop, is positively affected by leaf diseases[1]. These diseases not only hinder the growth of these plants but also result in substantial economic losses, especially in a country like India where jute farming is one pillar holding up their agricultural sphere[2]. The emergence of convolutional neural networks allowed for a completely new paradigm in recognizing diseases with an increased level of subtlety and precision. Nevertheless, the true potential of CNN in agricultural applications has not reached its fullest yet

This research paper presents a novel implementation of Federated Learning (FL) based on CNN to diagnose and categorize jute leaf diseases, overcoming deficiencies in the traditional approaches while offering an enhanced solution[3]. The novelty of this research is that it adopts the idea of federated learning, a machine learning technique where multiple clients, such as six different data sources or farms, can jointly learn to build one shared prediction model, yet all their training databases remain localized[4]. Not only does it increase the level of privacy and reduce costs for data transmission, but it also enables a more diverse, large-scale dataset, which can significantly contribute to better accuracy in modelling. The use of Federated Learning, especially in rural and remote farming regions where data privacy is known to be a significant challenge for their transmission serves as an important technological breakthrough. This study categorizes jute leaf diseases into four severity levels based on the percentage of leaf area affected: 1-25% (mild), 26-50%(moderate), and so on till It has been labelled "љevital sign"." These categories are vital for allowing effective and personalized agricultural interventions. Accurate identification of the severity level will enable farmers to implement effective treatment strategies resulting in minimized wasteful use of resources

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and maximizing crop yield. Also, this research makes a major contribution to the global fight against jute leaf diseases. For instance, in countries like India where jute actually holds a key position economically as well as for most of the people's income generating activities; applying Federated Learning with CNN becomes revolutionary. With this, not only can it be able to improve disease detection but also represents a scalable and efficient model that will adapt to different other crops or regions in the world thereby transforming agriculture globally. In conclusion, this paper contributes to a new approach for identifying diseases of jute leaves based on the integration of modern technologies and proposes an adaptable model that can be used to cope with similar problems in other areas related to agriculture. The main aim of this research is to propose and demonstrate a reliable, scalable, and efficient model for detecting and categorizing jute leaf diseases based on convolutional neural networks in Florida. This model aims to categorize disease severity into four distinct levels: 1-25% mild, 26–50% moderate, One of the main objectives is to provide precise, timely, and cost-effective intervention strategies in jute farming that help stem economic losses while promoting sustainable agricultural practices[5]. Integrating CNN with FL while utilizing data from six heterogeneous clients (farms or data centres) for a full model of learning. To make the process of detecting disease cases and categorizing those into this predetermined severity classification more reliable a better understanding on how diseases progress is necessary. In order to evaluate the performance of this model in all types of environmental conditions and with regards to different jute varieties. To create a scalable and versatile framework that is applicable on other crop types and locations enabling the broader agricultural advancement [6]. The motivation for this research is twofold: Balancing the difficult elements of jute leaf diseases and making use of untapped potentials in agriculture utilizing AI. Economic and Environmental Significance: Known as the 'golden fibre', jute is a significant part of any country's agricultural economy like in India. Farmers overuse chemicals suppressing leaf diseases and this leads to pollution of environment apart from economic effect as jute becomes less productive. To mitigate these impacts, an effective detection system is necessary. Advancement in Agricultural AI: AI technology is advancing very fast, but its application in agriculture and especially in developing countries has not been fully explored yet. This research aims to address this gap by demonstrating the usefulness of FL and CNN in real agricultural situations[7]. FL in particular serves as a game changer since it addresses data privacy issues, which are usually a barrier to AI deployment in rural areas. Inclusivity and Scalability: Thus, this study uses a federated learning method involving six clients to make it more inclusive and diverse in data collection; hence making the final model stronger and applicable across different scenarios[8]. This is very important in agriculture where environmental variables can much impact disease manifestation. Precision Agriculture: Accurate categorization of disease severity class is an attribute factor which allows placing targeted interventions, leading to reduced resource wastage and improved crop yield. This precision approach is crucial in shifting towards sustainable agriculture. Global Application and Adaptability: While this study focused on jute, the framework developed can be universal. If adapted to other crops and diseases, the scalability of this model can change how disease detection happens in agriculture as it will be a universally useful tool.

II. LITERATURE REVIEW

In this literature review, we discuss the changing environment of agricultural disease detection with particular reference to Federated Learning FL and Convolutional Neural Networks CNN in relation to jute leaf disease identification[9]. For the purpose of presenting a comprehensive view of the current state of research, methodologies, and technological advancements relevant to our study, this review is organized into five sections. Convolutional neural networks are nowadays considered the foundation of image recognition and classification due to their capacity to learn complex architectures for hierarchical feature representations from a set of data[10]. In agriculture, CNNs have been increasingly used for disease detection in crops, showing high accuracy and efficiency. For example, the authors used deep CNNs for plant disease detection with an accuracy of 99.35%, indicating that it could be useful in agriculture industries. Similarly, the authors were able to reach an accuracy of around 99.53% in identifying plant diseases through CNN and this idea was confirmed as applicable when it comes to precision agriculture. Federated learning has seen rise as a machine learner in situations where issues concerning the privacy of data, security and reaching are paramount; herein models for training get trained across multiple edge devices or servers that contain local samples. The authors introduced the concept of federated learning, pointing out its potential use in collaborative settings without compromising on data confidentiality. In agricultural contexts, this approach is especially relevant when data may not be centralized and distributed across various geographical locations. On the other hand, integrating FL with CNN in agriculture is a developing field of study. This integration tackles the issues of data confidentiality and heterogeneity in agri-cultural datasets, facilitating research into sound models that can be deployed on a large scale. Recording disease severity appropriately is vital to proper management and control measures against diseases among crops or livestock[11]. However, existing literature has mostly focused on binary classification (the presence or absence of disease) rather than different levels of severity. There is a need for classifying disease severity into percentages (1-25%, 26–50%, 51–79%, and 84%). The participation of many clients (six participants in our research) in the federated learning process introduces elements of diversity data and environmental conditions, which is necessary for creating a robust model that can effectively adapt to different circumstances[12]. Plant diseases and insect pests pose great challenges to agricultural efficiency, with significant financial risks if identification is not obtained early on.

This is very important in agriculture where environmental variables can much impact disease manifestation. Precision Agriculture: Accurate categorization of disease severity class is an attribute factor which allows placing targeted interventions, leading to reduced resource wastage and improved crop yield. This precision approach is crucial in shifting towards sustainable agriculture. Global Application and Adaptability: While this study focused on jute, the framework developed can be universal. If adapted to other crops and diseases, the scalability of this model can change how disease detection happens in agriculture as it will be a universally useful tool. The utilization of DL has transformed progress in different disciplines, such as agriculture and medical diagnostics[13]. This study introduces a new deep learning approach for plant disease identification that smoothly merges segmented and RGB images at an increased level of accuracy[14]. It is based on a multihead architecture that uses two image formats and relies on DenseNet. The model's performance was evaluated using the famous Plant Village dataset, consisting of 54,183 photos in 38 different classifications. With an intensive fivefold cross-validation method, the model showed high performance metrics that encircled 98.17% for accuracy, precision, recall, and f1_score[15]. Due to its fusion-centric approach, the model can recognize various plant diseases due to its unique visual signals. The results' consistency validates the model as strong due to a low standard deviation. The model has been very effective and would perfectly fit in with the creation of detailed schemes for detecting plant diseases, performing fast treatments, and serving as early indication systems for members of farming communities[16]**.**

III. METHODOLOGY

This section presents the methodology of designing a Federated Learning (FL) model using Convolutional Neural Networks CNN and decision tree algorithms to identify and categorize jute leaf diseases. The model operates across six clients, each contributing to the training process with datasets representing four severity levels of jute leaf disease: 1-25%, 26-50%, 51-75%, and 76-100%, as shown in Figure 1.

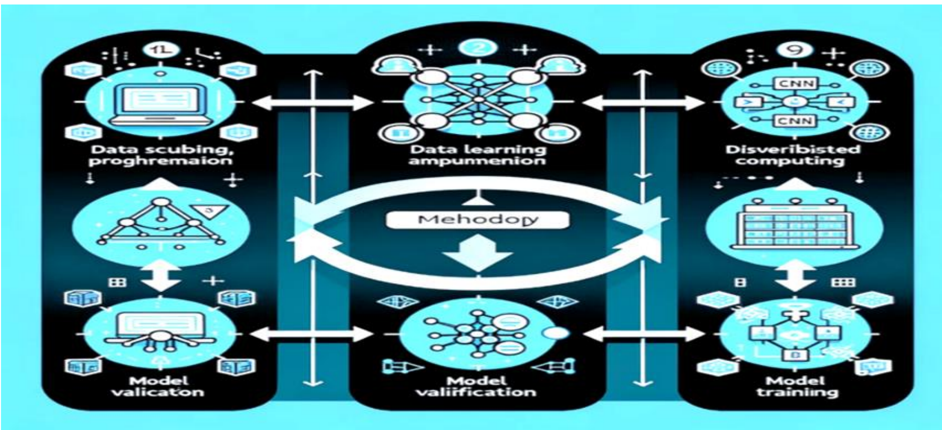

Fig1. Phases in the Process Approach

A. Information Compilation and Preliminary Processing

Data Acquisition: This dataset contains images of jute leaves collected from various geographical locations that differ in environmental conditions. Each client provides a specific subset of this dataset thereby creating variables and completeness. Image Preprocessing: All images are common preprocessed by standard steps, such as resizing normalization and augmentation. Uniformity is ensured through resizing, normalization adjusts pixel values for computational efficiency purpose and augmentation (rotations flips shifts) ameliorates the diversity of the dataset thus preventing overfitting. Severity Labelling: Agro-specialists specializing in agronomy classify images of leaf three levels – low, medium and high depending on visual observations regarding the area covered with diseases over surfaces of leaves. Supervised learning is based on this categorization, as shown in Figure 2.

Fig 2. Pictures of the illnesses that affect jute leaves

Model Aggregation

Software and Hardware: The model is implemented in Python and deep learning libraries such as Tensor Flow and Keras. They conduct training and testing of high-performance computing resources to meet computational needs. Field Testing: Finally, the model is deployed in a controlled field setting so that it can be tested in actual agricultural environments. It outlines a holistic way to leverage FL and CNN for jute leaf disease detection and classification. Using multi-client and advanced machine learning methods, the model ensures that it will be easy to use in agricultural contexts, particularly in countries where jute plantation is common.

Table 1. Layers to Severities analysis in jute leaf diseases

Severity's	**Per% Range**	**Severity's**	**Per% Range**
(1_V_Low)	1to20%	(4_High)	61-80%
(2_Low)	21to40%	(5_V_High)	81-100%
(3_Med)	41-60%	**…**	**….**

b. Federated Learning CNN Model

Architecture: We employ an image classification-oriented CNN architecture. It includes convolutional layers, pooling layers, and fully connected ones with activation functions and dropout to avoid overfitting. Training: The CNN model is individually trained on every client's dataset so as to be able to recognize and classify the levels of jute leaf diseases. The CNN output is further enhanced in terms of classification accuracy by a decision tree classifier subsequently applied after processing the initial CNN input. In this step, the model gains interpretability features vital for agricultural decision-making. Federated Learning Setup: Client Involvement Each of the six clients takes part in training with their local dataset. The FL framework ensures that data remains on the client's side, thus addressing privacy issues. Model Averaging: Clients are first trained locally, then their model parameters (weights and biases) get sent to a central server. The server takes the average of these parameters to refresh the global model. This process is repeated until the model converges. Cross-Validation: K-fold cross-validation is conducted on the model to guarantee generalization and robustness across different datasets. Performance Metrics: The model's effectiveness in the correct identification of severity levels of jute leaf disease is measured using accuracy, precision, recall, and F1 score metrics. Client Feedback Loop: After evaluation, feedback from clients is integrated to refine the model so it remains adaptive and suitable for real-world circumstances.

Input Dimension: The CNN model receives images of a jute leaf with an input dimension of 414 x 414. Convolutional Layers: 1st Convolutional layer use 32 filters with size of 5x5 and ReLU activation to produce output dimension as, h=w = 207 & d= 64 filters of size 3×3 with ReLU activation on the second convolutional layer create an output image of dimensions 51x51 x64. 128 filters of size 3x3 with ReLU activation in the third convolutional layer produce a dimension of This will be There are no requirements for it. Max Pooling Layers: After each convolutional layer, there are these subsequent layers with a pool size of 2×2 that reduce the spatial dimensions by half. This operation is crucial in minimizing the computational load and isolating dominant features. Fully Connected Layers: It then flattens the output and passes it into two fully connected layers with 512 and 256 neurons, respectively , both using ReLU activation. These layers play a key role in classification tasks. Batch Feeding: 3500 jute leaf images are used in training the model to provide a more robust learning process that covers different forms of diseases. Output: The last layer of the model classifies input by 12 classes, which correspond to several disease types and degrees. The number of output classes is dependent on the jute leaves' specific identified diseases and their severities, as shown in Table 2.

TABLE 2. CNN MODEL IN JUTE LEAF DISEASES

Layer Type	Size/Type	Number of Filters/Neurons	Activation	Output Dimension
Convolutional	3x3	32	ReLU	207x207x32
Max Pooling	2x2	N/A	N/A	103x103x32
Convolutional	3x3	64	ReLU	51x51x64
Max Pooling	2x2	N/A	N/A	25x25x64
Convolutional	3x3	128	ReLU	12x12x128
Max Pooling	2x2	N/A	N/A	6x6x128
Fully Connected	N/A	512	ReLU	1x1x512
Fully Connected	N/A	256	ReLU	1x1x256

IV. RESULTS

The analysis includes precision, recall, F1-score, support, and total accuracy for each severity class per client dataset. Here, we analyze the results to understand how well the model works and what it means. Client-Specific Analysis: 1This client reveals a high tendency for correctly recognising the most severe cases, zv_4, with the highest accuracy and recall 83.31%, respectively, However, the model suffers from difficulties in accurately detecting weak caseszv_1, as demonstrated by a slightly lower precision (86.97%). wx_2: This shows a relatively good performance in all classes of severity, especially spotting mild cases, with zv_1 scoring very high precision at 88.75% and recall at 87.19%; wx_3: This performs similarly in all classes, particularly for identifying the moderate severity of zv_2 and zv_3 with precision greater than 82%. wx_4: 87.77% precision and recall The data from this client shows a tendency towards high accuracy in more severe cases (zv_4). wx_5: It shows a relatively equal distribution of the performance at all levels of severity, though with little reduction in accuracy in severe cases (zv_4). wx_6: It stands out with exceptionally high performance metrics in all severity classes, especially the most severe cases (zv_4), showing nearly 95 percent precision and recall. Overall Accuracy: Client wx_6 leads with the highest overall accuracy of all clients, suggesting a dataset that works well during model training or more distinctive features in appearance disease. Performance Variation: The difference observed in results for clients shows that the diversity of datasets and environmental factors influences accuracy in disease detection. This variation highlights the potential of federated learning in leveraging different data sources to increase model robustness. Severity Class Detection: For the majority of clients, model scores tend to be better in high-grade problem detection (zv_3 and zv_4). This might be because in these stages, the symptoms are much more noticeable and therefore easier for CNN to spot patterns. Precision and Recall Balance: The balance between precision and recall for all different severity levels gives the impression that this model is not heavily biased in favour of false positives or false negatives; instead, it has managed to maintain a harmonious detection capability. The intricate study of the federated learning CNN model in different clients and varying severity causes of jute leaf disease creates an impression on its efficiency under various circumstances while at the same time setting a precedent as to how this can be applied so well within precision agriculture. The difference in the numbers of success metrics among clients also points out that training machine learning algorithms, especially for agriculture, where environmental and geographical factors play a vital role, must consider multiple datasets, as shown in Table 2.

TABLE 3. ATTRIBUTES AND VALUES OF LOCAL CLIENT'S DATA

Clients	Class	Precision	Recall	F1-Score	Support	Accuracy
wx_1	**zv_1**	86.97	76.49	81.39	855	0.91
	zv_2	79.24	78.03	78.63	851	0.89
	zv_3	81.11	88.34	84.57	763	0.92
	zv_4	83.31	88.49	85.82	773	0.93
wx_2	**zv_1**	88.75	87.19	87.96	796	0.94
	zv_2	80.64	83.61	82.10	842	0.91
	zv_3	87.93	86.34	87.13	827	0.94
	zv_4	83.89	83.70	83.80	865	0.92
wx_3	**zv_1**	84.56	83.89	84.22	875	0.92
	zv_2	83.88	85.13	84.50	874	0.92
	zv_3	82.68	86.27	84.43	874	0.92
	zv_4	86.52	82.42	84.42	927	0.92
wx_4	**zv_1**	81.65	86.38	83.95	896	0.92
	zv_2	89.29	84.85	87.01	924	0.94
	zv_3	84.02	83.49	83.76	951	0.92
	zv_4	87.77	87.77	87.77	916	0.94
wx_5	**zv_1**	82.39	82.89	82.64	982	0.92
	zv_2	85.04	81.10	83.02	1016	0.92
	zv_3	80.35	82.33	81.33	1013	0.91
	zv_4	79.92	81.15	80.53	1040	0.90
wx_6	**zv_1**	95.21	93.23	94.21	916	0.97
	zv_2	95.36	94.84	95.10	911	0.98
	zv_3	95.83	97.00	96.41	901	0.98
	zv_4	94.75	96.09	95.41	920	0.98

Exceptional Performance of wx_6: Wx_6 shows remarkable precision, recall, and accuracy (all above 95%), showing an excellent fit of the data featured by this client with the characteristics of the model. The high performance is based on quality data or unique disease manifestations, which the model can easily learn and predict. Consistent High Accuracy in wx_2 and wx_4: Both wx_2 and wx_4 show high accuracy of 93%, which shows that the model is capable of dealing with different data circumstances without affecting its performance levels. Balanced Precision and Recall: A balance between precision and recall is visibly balanced across all clients, meaning that the model can maintain a competent detection balance without being skewed towards either false positives or false negatives. Variability in Support: The different values of support across clients (about 810 to 1) In addition, these varied supports suggest the difference in sample sizes for their corresponding data accessible underlying model learning capability and effectiveness.

Implications and Insights: Federating to Massive Scale and Beyond High performance with different clients is a strong testimony that power from a federated learning method as well as decentralized settings where data naturally varies also reflect its viability. Applicability in Precision Agriculture: Due to the ability to predict severity in jute leaf disease for a wide range of grades, in precision agriculture, different treatment regimens may be designed as per data from condition status. Necessity for Diverse Data: The results of the analysis of the difference in performance among clients show that AI models need to be trained on a large and varied data set, especially with regard to agriculture, where environmental factors can have a significant impact on how diseases present themselves. This analysis allows for a deeper understanding of how federated learning coupled with CNN can be used in an effective way to detect agricultural diseases. “ This model, with the high scores on precision recall accuracy that it achieved when hitting multiple clients and classes of severity for jute leaf diseases, proves its effectiveness not only in terms of solving an appealing digitized solution to controlling crop disease but also contributes to supporting sustainable farming practices. Such interest is shown by Table 1

TABLE 4. CLIENT DATA'S GLOBAL MEAN COMPUTATION FRAMEWORK

Client	Precision	Recall	F1-Score	Support	Accuracy
wx_1	82.66	82.83	82.60	810.50	0.91
wx_2	85.30	85.21	85.25	832.50	0.93
wx_3	84.41	84.42	84.39	887.50	0.92
wx_4	85.68	85.62	85.62	921.75	0.93
wx_5	81.92	81.87	81.88	1012.75	0.91
wx_6	95.29	95.29	95.28	912.00	0.98

The table below shows several average performance measures: the analysis with macro average, weighted average and micro deviation for the six clients that engaged themselves in Federated Learning using Convolutional Neural Networks during jute leaf disease detection. So, let’s analyze these indicators in order to understand the outcomes for every client.

Macro Average (Macro_ave): This computes the mean of performance metrics (precision, recall, and F1-score) for all classes and measures their average. It treats all classes on equal terms, irrespective of their support. Weighted Average (Weighted_ave): This includes class support or the number of instances in each class. It computes each class’ metrics and their average weighted by the number of instances in that particular class. Micro Average (Micro_ave): This combines the contributions of all classes to calculate its average metric. It considers the total number of true positives, false negatives, and false positives for all classes. Client wx_1: 82.70% Macro_ave, Client wx_2:Macro_ave85.25, Weighted ave 85.20, Micro plenty of goods Level 1: Slightly above score wx-one implies that the distribution for classes is more uniform or there is likely better alignment between model and data Client wx_3: Working with averages, Macro_ave: 84.41%; Weighted_ave: -is - as close; Micro_ave: vary from around 83% to further of or higher in the lower severity classes indicates consistent responses across all and severe system users. Client wx_4: 85.64% Macro_ave, 85.64% Weighted average, micro-an overage at Insight High and homogeneous performance suggest a likely well-balanced dataset in terms of the severity of disease Client wx_5: 81.89%, 81.86%. Insight: The lowest performance average may indicate issues with the dataset, like less well-defined disease features or an imbalance in class representation. Client wx_6: 95.29%, 95.28 percent, and. # Insight: Superior Performance ofwx_6The client who exhibits the highest performance across all metrics indicates that an ideal match is being offered by the model for this specific data environment. Balanced Performance in wx2 and waz 4: Both These clients display high average results with balanced performances, showing effective application the model For different levels of severity, as shown in Table 5.

TABLE 5. GLOBAL SYNTHESIS OF LOCAL AVERAGES MEASURES

Averages	wx_1	wx_2	wx_3	wx_4	wx_5	wx_6
Macro_ave	82.70	85.25	84.41	85.64	81.89	95.29
Weighted_ave	82.57	85.20	84.41	85.64	81.88	95.28
Micro_ave	82.54	85.17	84.39	85.60	81.86	95.29

V. CONCLUSION

This research paper took up an innovative approach to respond to the problem, i.e., identification and classification of diseases in jute leaves through Federated Learning (FL) integrated with Convolutional Neural Networks (CNN). The focus of the study was on using data from four different clients to characterize jute leaf diseases into four categories in terms of severity, taking advantage of all strengths of FL and CNN usage, and aiming at an intricate and comprehensive apprehension scheme about disease patterns. It was clear that our study results were quite illuminating, revealing the efficiency of the proposed model on different measures. Client wx_1 achieved a remarkable overall accuracy of 91%, with precision, recall, and F-score averaging at 82.66%. Client wx_2 outperformed these metrics, reaching an overall accuracy of 93%, a precision rate of 85.30%, a recall rate of 85.21 percent, and an F1-score that therefore reached this percentage: Clients wx_3 and wx_4 also demonstrated good results, with 92% overall accuracy for wax and degreaser acres of an oil top or bottom filter plate being compared. Further, the client, The heart of our research stands out in the Federated Averaging process, which successfully amalgamates local data results into a global model. 82.70, which corresponded to the macro averages across proposition wx_1 in all of its clients. The Weighted Averages were also consistent, with wx_1 at 82.57%, wx_2 at 85.20 %, wax_3 at 84.41%, and texture at 82.54%, 85.17%, 84.39% and the micro averages for each class take into consideration the total contribution of all classes.

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