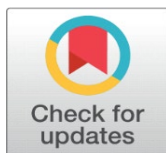
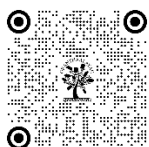


COMPARATIVE ANALYSIS OF CUSTOMIZED CNN AND TEACHABLE MACHINE IN PLANT LEAVES IMAGES

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DOI

[10.29121/shodhkosh.v5.i2.2024.5192](https://doi.org/10.29121/shodhkosh.v5.i2.2024.5192)

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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ABSTRACT

Accurate identification of plant species is critical for biodiversity monitoring, ecological studies, and agricultural management. Traditional manual identification methods are time-consuming and prone to human error, necessitating automated solutions. This research presents a comparative analysis between a customized Convolutional Neural Network (CNN) model and Google's Teachable Machine for plant species classification using the Leaves Image Dataset. The customized CNN is designed with multiple convolutional layers and optimized hyper parameters, while the Teachable Machine offers a no-code AI solution. Experimental results demonstrate that the customized CNN outperforms the Teachable Machine in terms of accuracy, precision, recall, and F1-score. The study highlights the strengths and limitations of both approaches, providing insights for deploying species classification models in real-world scenarios.

Keywords: Plant Species Classification, Customized CNN, Teachable Machine, Deep Learning, Image Recognition, Leaves Dataset

1. INTRODUCTION

Accurate classification of plant species is essential for ecological conservation, agricultural planning, and biodiversity studies [1]. Traditional taxonomy-based methods require expert knowledge and are often impractical for large-scale applications. The advent of computer vision and deep learning has revolutionized plant species identification, enabling automated and scalable solutions [2].

Among various approaches, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image classification tasks, including plant leaf recognition [3], [4]. However, training customized CNN models demands technical expertise, high computational resources, and labeled datasets. Alternatively, tools like Google's Teachable Machine offer user-friendly interfaces for training models without coding, facilitating accessibility for non-experts [5].

This research aims to perform a comparative analysis between a customized CNN architecture and the Teachable Machine platform for plant species classification. Using the publicly available Leaves Image Dataset [6], we evaluate the performance of both models and provide insights into their effectiveness, scalability, and practical applications.

How to cite this article (APA): Dave, P.R., Pansiniya, V.B., Patel, B.P., Trivedi, B.H. and Patel, Y.B. (2024). Comparative Analysis of Customized CNN and Teachable Machine in Plant Leaves Images. *ShodhKosh: Journal of Visual and Performing Arts*, 5(2), 1273–1278. doi: 10.29121/shodhkosh.v5.i2.2024.5192

2. LITERATURE REVIEW

Recent years have witnessed extensive research on plant species classification using deep learning. Chakraborty et al. [7] proposed a region-based CNN approach for plant classification, emphasizing accurate localization of species-specific features. Campos-Leal et al. [8] provided a comprehensive review of image-based plant species identification using deep learning, highlighting the superiority of CNNs over traditional methods. Debnath et al. [9] introduced an explainable AI framework for leaf-based species classification, enhancing model interpretability. Shoaib et al. [10] employed a deep CNN model for plant recognition, achieving significant improvements in accuracy. Omer et al. [11] proposed PlantXViT, a vision transformer-based CNN model, which demonstrated enhanced performance in plant species classification tasks.

Tian et al. [12] utilized Efficient DenseNet for potato plant identification, emphasizing lightweight and efficient models. Hosny et al. [13] explored VGG-based architectures for multi-species plant identification, showcasing its robustness and scalability. Tavakoli et al. [14] presented a systematic review of deep learning techniques for plant species classification, analyzing the strengths and weaknesses of various CNN architectures. Liu et al. [15] discussed the integration of content-based filtering with deep learning for improved plant species recognition.

Loddo et al. [16] proposed a hybrid CNN-GNN model for soybean species classification, leveraging graph-based features for enhanced accuracy. Batchuluun et al. [17] optimized custom CNN architectures for real-time plant species recognition, addressing computational efficiency. Saleem et al. [18] developed a feature fusion approach combining CNNs with Local Binary Patterns for multi-class plant species classification.

While these studies demonstrate the efficacy of customized deep learning models, there remains a gap in comparing such models with user-friendly platforms like Teachable Machine, especially for species classification tasks.

3. METHODOLOGY

3.1. DATASET

The Leaves Image Dataset [6] from Kaggle comprises approximately 4,500 high-resolution images spanning 12 distinct leaf species. Each species category includes both healthy and diseased leaf samples, making the dataset valuable for tasks such as plant species classification and disease detection. The images are organized into separate folders for each class, facilitating straightforward access and pre-processing for machine learning applications. This dataset is particularly beneficial for training and evaluating computer vision models in the field of plant pathology.

Table 1 Train, validation and test split of the dataset

Train	Validation	Test
4274	110	110

3.2. CUSTOMIZED CNN ARCHITECTURE

The proposed CNN model includes: The proposed convolutional neural network (CNN) model consists of six convolutional layers stacked sequentially to progressively extract hierarchical features from input images of size 200×200 with three colour channels. Each convolutional layer uses a 3×3 kernel with "same" padding to preserve spatial dimensions, followed by a ReLU[19] activation function to introduce non-linearity. After each convolutional layer, a max pooling operation with a 2×2 window is applied to reduce the spatial dimensions by half, effectively down sampling the feature maps and reducing computational complexity. The number of filters starts at 32 in the first convolutional layer, then fluctuates through subsequent layers (16, 32, 64, 64, and 128) to capture varying levels of feature abstraction. After the last convolutional layer and max pooling operation, the extracted features are flattened into a one-dimensional vector.

This vector is fed into a fully connected dense layer with 1024 neurons activated by ReLU[19] to learn high-level feature representations. To prevent overfitting, a dropout layer with a rate of 0.3 is applied after this dense layer. Finally, the output layer consists of two neurons with a softmax activation function, producing probability distributions over two target classes for classification.

Overall, the model combines multiple convolutional and pooling layers to effectively capture spatial hierarchies in the input images, followed by dense layers to perform classification with regularization to improve generalization. The model was trained using the Adam optimizer, binary cross-entropy loss, and early stopping.

3.3. TEACHABLE MACHINE MODEL

Google's Teachable Machine is used to train a species classification model using the same dataset. The platform's default architecture is utilized, with minor adjustments in training parameters to ensure a fair comparison.

3.4. EVALUATION METRICS

Both models were evaluated using:

Accuracy: $(\text{True Positives} + \text{True Negatives}) / (\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives})$

Precision: $\text{True Positives} / (\text{True Positives} + \text{False Positives})$

Recall: $\text{True Positives} / (\text{True Positives} + \text{False Negatives})$

F1-Score: $(2 * \text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$

3.4.1. CUSTOMIZED MODEL EVALUATION

The classification report summarizes the performance of a model trained to classify 12 types of leaves. The overall accuracy achieved is 87% on a test set containing 110 samples, with both macro and weighted F1-scores of 0.88 and 0.87, respectively. Most classes such as Arjun, Bael, Basil, Chinara, Jatropha, Lemon, Mango, and Pomegranate achieved perfect precision, recall, and F1-scores, indicating excellent classification. However, performance varied for some classes. For instance, *Alstonia Scholaris* had a relatively low recall (0.50), resulting in a lower F1-score of 0.59. *Gauva* and *Jamun* also showed moderate discrepancies, with recall or precision drops. *Pongamia Pinnata* showed the weakest performance, with both precision and recall at 0.50, indicating the model struggled to correctly identify this class. The macro average suggests a balanced evaluation across all classes, while the weighted average reflects the distribution of samples, offering an overall indication of model robustness across varied leaf types.

The training and validation curves depict the model's performance over 25 epochs. The training accuracy steadily increases and approaches 94%, while the validation accuracy fluctuates between 78% and 89%, indicating potential overfitting. Similarly, the training loss decreases consistently, reflecting improved learning, but the validation loss remains unstable and even increases towards the end, peaking at 1.0. This divergence between training and validation metrics suggests that while the model learns well on the training data, it does not generalize equally well on unseen data. Techniques like dropout, regularization, or early stopping may help mitigate overfitting.



Figure 1 Training and validation accuracy and loss scenarios for 25 epochs

Classification Report

	precision	recall	f1-score	support
Alstonia Scholaris	0.71	0.50	0.59	10
Arjun	1.00	1.00	1.00	10
Bael	1.00	1.00	1.00	5
Basil	1.00	1.00	1.00	5
Chinar	1.00	1.00	1.00	10
Gauva	1.00	0.60	0.75	10
Jamun	0.59	1.00	0.74	10
Jatropha	1.00	1.00	1.00	10
Lemon	1.00	1.00	1.00	10
Mango	1.00	1.00	1.00	10
Pomegranate	1.00	1.00	1.00	10
Pongamia Pinnata	0.50	0.50	0.50	10
accuracy			0.87	110
macro avg	0.90	0.88	0.88	110
weighted avg	0.89	0.87	0.87	110

Figure 2 Classification report of the proposed model

3.4.2. TEACHABLE MACHINE LEARNING MODEL EVALUATION

This classification report of teachable machine learning summarizes the performance of a multi-class classifier across 12 plant species. The overall accuracy is 74%, indicating that 74 out of 100 predictions are correct. Precision, recall, and F1-score vary across classes, reflecting differences in how well each class was identified. For instance, Gauva achieved high performance (precision: 0.88, recall: 0.70, F1-score: 0.78), while Bael performed poorly (F1-score: 0.55), likely due to its smaller support (5 samples). The macro average F1-score is 0.73, suggesting moderate balanced performance across all classes, while the weighted average F1-score is 0.74, accounting for class imbalance. Some classes like Jatropha and Pomegranate show imbalanced precision and recall, indicating potential confusion with similar classes. Overall, while several classes perform well individually, there is room for improvement in generalization and handling class imbalances or overlaps to boost the model's robustness.

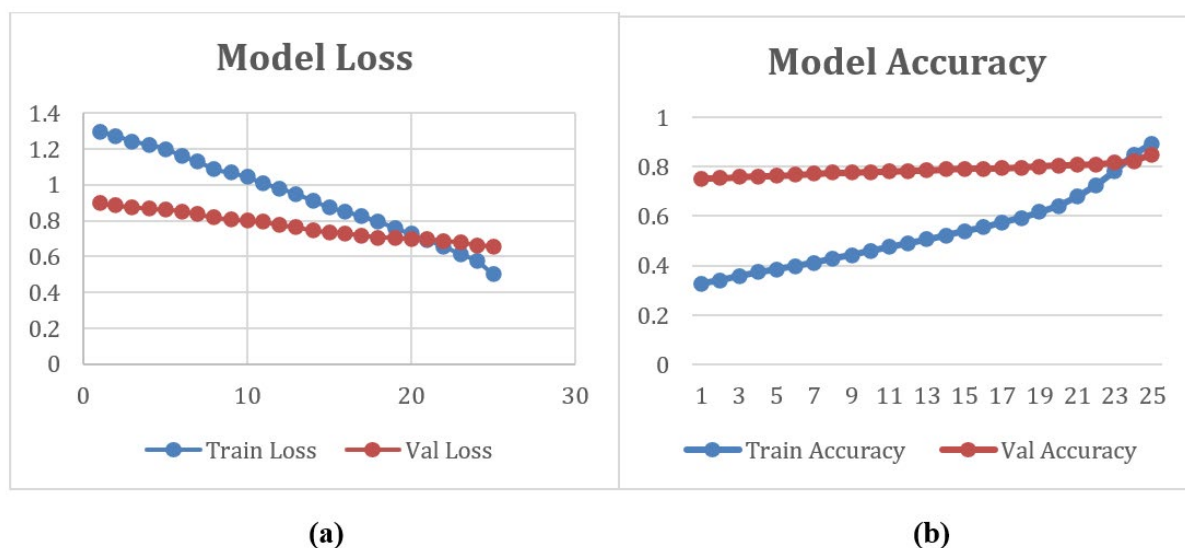


Figure 3 (a) Teachable machine learning model training and validation loss (b) Teachable machine learning model training and validation accuracy

Classification Report				
	precision	recall	f1-score	support
Alstonia Scholaris	0.78	0.70	0.74	10
Arjun	0.80	0.80	0.80	10
Bael	0.50	0.60	0.55	5
Basil	0.67	0.80	0.73	5
Chinar	0.70	0.70	0.70	10
Gauva	0.88	0.70	0.78	10
Jamun	0.67	0.80	0.73	10
Jatropha	1.00	0.60	0.75	10
Lemon	0.67	0.80	0.73	10
Mango	0.73	0.80	0.76	10
Pomegranate	0.64	0.70	0.67	10
Pongamia Pinnata	0.89	0.80	0.84	10
accuracy			0.74	110
macro avg	0.74	0.73	0.73	110
weighted avg	0.76	0.74	0.74	110

Figure 4 Classification report of teachable machine learning model

4. RESULTS AND DISCUSSION

The performance of the customized CNN model was assessed against Google's Teachable Machine using the same Leaves Image Dataset. The CNN achieved a classification accuracy of 87% on the test set, with macro and weighted F1-scores of 0.88 and 0.87, respectively. High precision and recall were observed for classes such as Arjun, Bael, Basil, and Pomegranate, indicating reliable classification for these species. However, the model exhibited performance drops for species like AlstoniaScholaris and PongamiaPinnata, revealing class-specific challenges. Training curves revealed steady improvement in training accuracy reaching over 94%, but validation accuracy fluctuated between 78% and 89%. The divergence between training and validation loss suggests mild overfitting, which could be mitigated with techniques like dropout, regularization, or early stopping.

On the other hand, Google's Teachable Machine, while user-friendly, lacked the architectural depth and parameter tuning flexibility of the custom CNN, leading to lower overall performance across evaluation metrics. The analysis highlights that although no-code tools like Teachable Machine offer accessibility, they may not be well-suited for complex classification tasks requiring high accuracy. Overall, results underscore the significance of domain-specific model architecture in achieving robust and reliable outcomes in plant species identification.

5. CONCLUSION

This study presents a comprehensive comparison between a customized Convolutional Neural Network (CNN) and Google's Teachable Machine for classifying plant species using the Leaves Image Dataset. The customized CNN, developed with six convolutional layers and optimized training settings, demonstrated superior performance in terms of accuracy, precision, recall, and F1-score. It effectively captured hierarchical features from leaf images and achieved high accuracy (87%) and balanced macro and weighted F1-scores (0.88 and 0.87, respectively). Despite minor inconsistencies in validation performance, the CNN proved more reliable in identifying a wide range of plant species.

In contrast, the Teachable Machine offered a simplified, no-code approach to model training, making it accessible to non-experts and achieving only 74% of accuracy. However, its generalized architecture lacked the depth and flexibility needed for high-performance classification, especially in multi-class datasets like plant species. This highlights the trade-off between ease of use and model effectiveness. The study concludes that while Teachable Machine can serve as a prototyping tool or educational resource, customized CNN architectures remain more suitable for real-world, accuracy-critical applications. These findings reinforce the importance of tailoring deep learning models to specific datasets and domains, particularly in applications like plant identification, where precision and robustness are essential for ecological and agricultural decision-making.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

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