Machine Learning-Based Classification of Economically Important Herbal Plants Using Google Teachable Machine

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Abstract

Accurate plant identification is crucial for sustainable utilization and its conservation, particularly in biodiversity-rich regions such as Northeast India. Traditional methods rely on expert knowledge and physical herbarium collections, which can be time-consuming and prone to human error. Machine learning (ML) offers a promising alternative, automating species recognition through image classification. This study explores the application of Google Teachable Machine (GTM) for classifying economically important herbal plants, namely Aloe vera, Amla, Hibiscus, Neem, Pepper, and Mint. A total of 920 images were utilised, following strict selection criteria to enhance model accuracy. Images were preprocessed based on clarity, background simplicity, lighting, and varied angles. GTM, a user-friendly, codeless ML tool, was employed to train a deep learning model for plant classification. The dataset was automatically split into training (80%) and testing (20%) subsets, ensuring robust evaluation. Findings highlight GTM's potential as an accessible and efficient tool for plant species identification, offering rapid classification without extensive computational resources. This study underscores the significance of AI-driven approaches in botany, particularly in regions lacking plant taxonomists, and provides a foundation for future applications of ML in herbal plant research.

Keywords: Herbal plants, Google's Teachable Machine, Codeless nueral network, Convulation neural networking

Introduction

Precise plant identification is indispensible, and enables for its sustainable utilization and conservation (Ganesh et al., 2025, p. 1). Traditionally, this process involves expert evaluation, field visits, and the creation of herbarium collections — methods that are often time-consuming, resource-intensive, and prone to human error, particularly when handling large datasets (Gowthaman & Das, 2025, p. 2). Another added challenge is the unavailability of plant taxonomy experts on-site, leading to difficulties in accurate plant identification. This is particularly relevant in the Northeastern states of India, including Nagaland, which host a diverse range of endemic plant species (Deb et al., 2019, p. 1; Keretsu et al., 2022, p. 1).

Machine learning (ML) has emerged as a transformative technology that can significantly enhance plant identification. As a subset of artificial intelligence (AI), ML enables computer systems to learn from datasets—including images, audio, and videos—and operate autonomously (Onan, *et al.,* 2016, p. 232; Onan, 2019, p. 293). By leveraging complex algorithms, ML-based models can automate plant classification, making the process faster and more efficient as compared to traditional methods (Nunavath & Danilin, 2024, p. 1; Gowthaman & Das, 2025, p. 1). Among the various ML techniques, neural networks are gaining popularity as they mimic the human brain, recognizing patterns and making accurate predictions without requiring predefined rules (Montesinos et al., 2022, p. 1; Delos, 2019, p. 3208).

While early ML models required advanced programming skills, particularly expertise in coding languages, recent advancements have made these tools more accessible. Google's Teachable Machine (GTM) is one such platform that simplifies deep learning by offering a codeless, user-friendly interface, allowing researchers to train models without programming expertise (Wong & Fadzly, 2022, p. 1097). This democratization of machine learning may make plant identification more efficient, reducing reliance on manual classification while ensuring greater accuracy and scalability.

GTM is a cloud web based tool that enables users to create ML models without any coding experience. The GTM has inbuilt metrics for model assessment and also allows for exporting the models for further modification (Wong & Fadzly, 2022, p. 1101). Thus, GTM ability to create customized models using user-generated datasets is one of its key advantages. Unlike cloud services such as Google Lens, which depends on external sources and pre-trained databases for image recognition, GTM allows users to train models based on specific plant samples, ensuring greater accuracy and control over classification results. Thus, while services such as Google Lens, while useful for general plant identification, may provide inconsistent or unreliable results due to its reliance on publicly available images, which may contain misclassified or regionally irrelevant data. This limitation makes it unsuitable for scientific research that requires precise, reproducible, and context-specific identification. Keeping in view that GTM, in contrast, enables researchers to develop tailored models by incorporating high-quality, standardized images under controlled conditions, such as consistent lighting, backgrounds, and angles. This controlled dataset approach minimizes classification errors and enhances accuracy (Malahina, 2023, p. 280). Additionally, GTM's cloud-based infrastructure ensures rapid model training and deployment without the need for high-end computing hardware, making it a practical solution for researchers with limited computational resources (Wong & Fadzly, 2022, p. 1101). Given these advantages, this study explores the application of GTM in the classification of herbal plants, assessing its accuracy, efficiency, and suitability for botanical research. By leveraging deep learning through a codeless platform, researchers can streamline species identification while mitigating the challenges posed by conventional methods and general-purpose recognition tools.

Methodology

- Herbal plant dataset:

A total of 920 images were collected for training and testing purposes. The selected plant species included Aloe vera, Amla, Hibiscus, Neem, Pepper, and Mint, all of which are economically significant herbal plants. The dataset was sourced from Pushpa and Shobha (2023), specifically from their Indian Plant Dataset available on Kaggle repository.

- Image Selection Criteria:

To ensure optimal model performance, careful consideration was given to image selection. The selection criteria were based on the recommendations of Wong and Fadzly (2022, p. 1100), which emphasize factors that improve machine learning accuracy in image classification tasks:

1. Clear Representation of the Plant Specimen – Images containing blurry or indistinct plant features were excluded to ensure the model could accurately detect and classify each species.
2. Minimal Background Complexity – Images with cluttered or highly textured backgrounds were removed to prevent background interference, as complex backgrounds may lead to false feature recognition by the model.
3. Adequate Lighting Conditions – Only well-lit images were

selected, avoiding overly dark or overly bright images that could affect model performance.

4. Multiple Angles and Perspectives – A variety of images showcasing different angles of the same plant species were included to improve model robustness and generalizability.

- Google's Teachable Machine (GTM):

GTM is a web-based machine learning platform accessible at www.teachablemachine.withgoogle.com, designed to simplify the creation of machine learning models based on TensorFlow (Figure 1 in page 109). One of GTM's most notable features is its codeless implementation, which eliminates the need for programming expertise, allowing users with limited or no coding experience to develop and deploy machine learning models. GTM provides an intuitive interface where users can upload image datasets and categorize them into distinct classes, forming the basis for supervised learning models. The classification process is structured into three key steps: (1) data collection and labeling, where images are grouped into specific categories; (2) model training, which involves defining hyperparameters such as the number of epochs, batch size, and learning rate; and (3) model evaluation, where accuracy and classification performance are assessed based on the training data. Once the model is trained, GTM offers multiple export options, including TensorFlow.js, TensorFlow Lite, and TensorFlow SavedModel, enabling seamless integration into various applications. The TensorFlow.js format is particularly advantageous for web based deployment and mobile applications, facilitating real-time inference with minimal computational resources. Additionally, GTM allows users to fine-tune their models post-training, ensuring improved accuracy and adaptability to new data. The simplicity and accessibility of GTM make it an ideal tool for rapid prototyping and real-world deployment of machine learning models in various domains (Wong & Fadzly, 2022, p. 1100).

- Data Splitting and Processing in Google Teachable Machine (GTM):

GTM automatically splits the dataset into training and testing subsets to evaluate model performance. Typically, the training set is used to teach the model how to recognize plant species, while the test set is used to assess its accuracy on unseen data. This split ensures that the model does not merely memorize the images but instead learns to identify patterns that generalize well to new inputs. The ratio of data splitting in GTM is typically 80% for training and 20% for testing, although this can be adjusted manually if needed.

- Convolutional Neural Network (CNN):

GTM leverages Convolutional Neural Networks (CNNs) to enable efficient image classification without requiring users to manually implement complex deep-learning algorithms (Toivonen et al., 2020, p. 308). CNNs are a class of deep neural networks specifically designed for processing structured grid data, such as images (Zhang, et al., 2018, p. 1842) . The CNN architecture in GTM consists of multiple layers, including the input layer, convolutional layers, pooling layers, and fully connected layers, each playing a crucial role in feature extraction and classification as depicted in Figure 2 in page 109 (Malahina et al., 2024, p. 534). The input layer receives raw image data, which is subsequently processed by the convolutional layers. These layers utilize filters to extract important features such as edges, textures, and patterns from the input images. The application of multiple convolutional layers allows the network to learn hierarchical feature representations, enhancing its ability to differentiate between various image classes.

Pooling layers, typically using max-pooling or average-pooling techniques, follow the convolutional layers. These layers reduce the spatial dimensions of the feature maps while retaining essential information, thereby improving computational efficiency and mitigating the risk of overfitting. Pooling helps the network focus on the most relevant features, making it robust to variations such as image rotation, scaling, and noise (Zafar et al., 2022, p. 8644).

The final stage of the CNN architecture is the fully connected layer, which serves as the classifier. This layer transforms the high-level feature representations learned by the convolutional and pooling layers into class predictions. By leveraging backpropagation and optimization algorithms, such as stochastic gradient descent (SGD) or Adam, the network adjusts its weights iteratively to minimize classification errors and enhance accuracy (Malahina et al., 2024, 532). Overall, GTM's integration of CNNs provides a user-friendly yet powerful approach to image classification, bridging the gap between sophisticated deep learning techniques and accessibility for non-experts. The ability to train and deploy CNN-based models without extensive programming knowledge makes GTM a valuable tool for educational, research, and practical applications in computer vision.

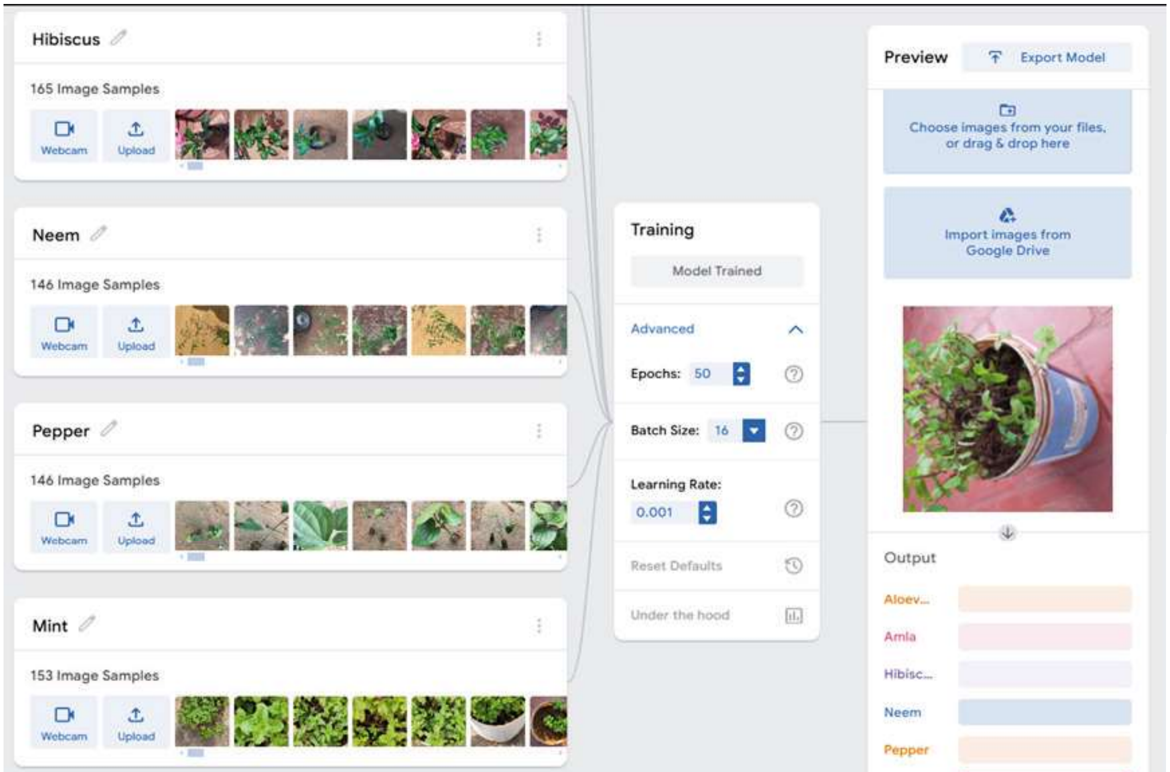

Figure 1: Overview of Google Teachable Machine

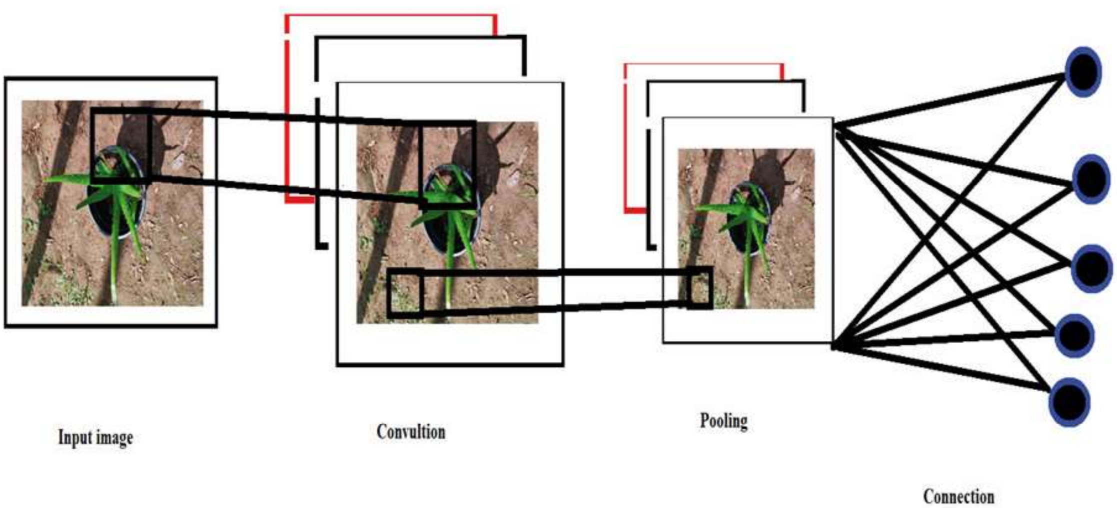

Figure 2: Architecture of the CNN

Result and discussion

To assess the accuracy of the trained model, the built-in evaluation metrics provided by GTM were utilized as per Wong & Fadzly (2022, p. 1101). Figure 3 illustrates the various performance metrics analyzed in this study. These include the confusion matrix (Figure 3i in page 111), which represents the number of correct and incorrect predictions made by the model compared to the actual dataset used in testing. The confusion matrix provides a clear visualization of the model's classification accuracy by showing the distribution of correctly and incorrectly classified images. In the present study, the confusion matrix indicated a high degree of accuracy, demonstrating the robustness of the model's predictive capabilities. Additionally, the accuracy plot (Figure 3iii in page 111) revealed consistently high prediction success rates, while the epoch score (Figure 3ii in page 111) remained low, further affirming the efficiency of the training process. The high model accuracy can be attributed to several key factors, including adequate lighting, a consistent background, and high-quality images used during training.

According to Wong & Fadzly (2022, p. 1104), distinct morphological variations among specimens in an image dataset can significantly impact classification accuracy. Factors such as specimen color variations under different lighting conditions have been reported to influence prediction reliability. In the current study, the use of a consistent background likely contributed to the high classification accuracy, as inconsistent backgrounds can sometimes be incorrectly identified as distinguishing features by machine learning models (Fadzly et al., 2021). Algorithms such as GTM may inadvertently focus on background details instead of the primary image subject, leading to misclassification. The present study mitigated this issue by ensuring uniform backgrounds, thereby reducing errors in the confusion matrix.

This observation has two key implications. First, when using varied backgrounds in image classification tasks, it is crucial to include a sufficiently large and diverse training dataset to enhance generalizability. Second, maintaining a consistent background improves the reliability of predictions, ensuring more robust model performance. Another critical factor influencing model accuracy is the quality and resolution of the images. While measures were taken to ensure a uniform background, unavoidable variations in environmental conditions can still pose challenges, particularly when images are collected from diverse field locations. To address this, images in the dataset were captured from multiple angles with minimal background interference, improving classification robustness. Additionally, the use of uniform image resolutions across all samples ensured optimal image quality, reducing potential discrepancies in feature extraction and classification.

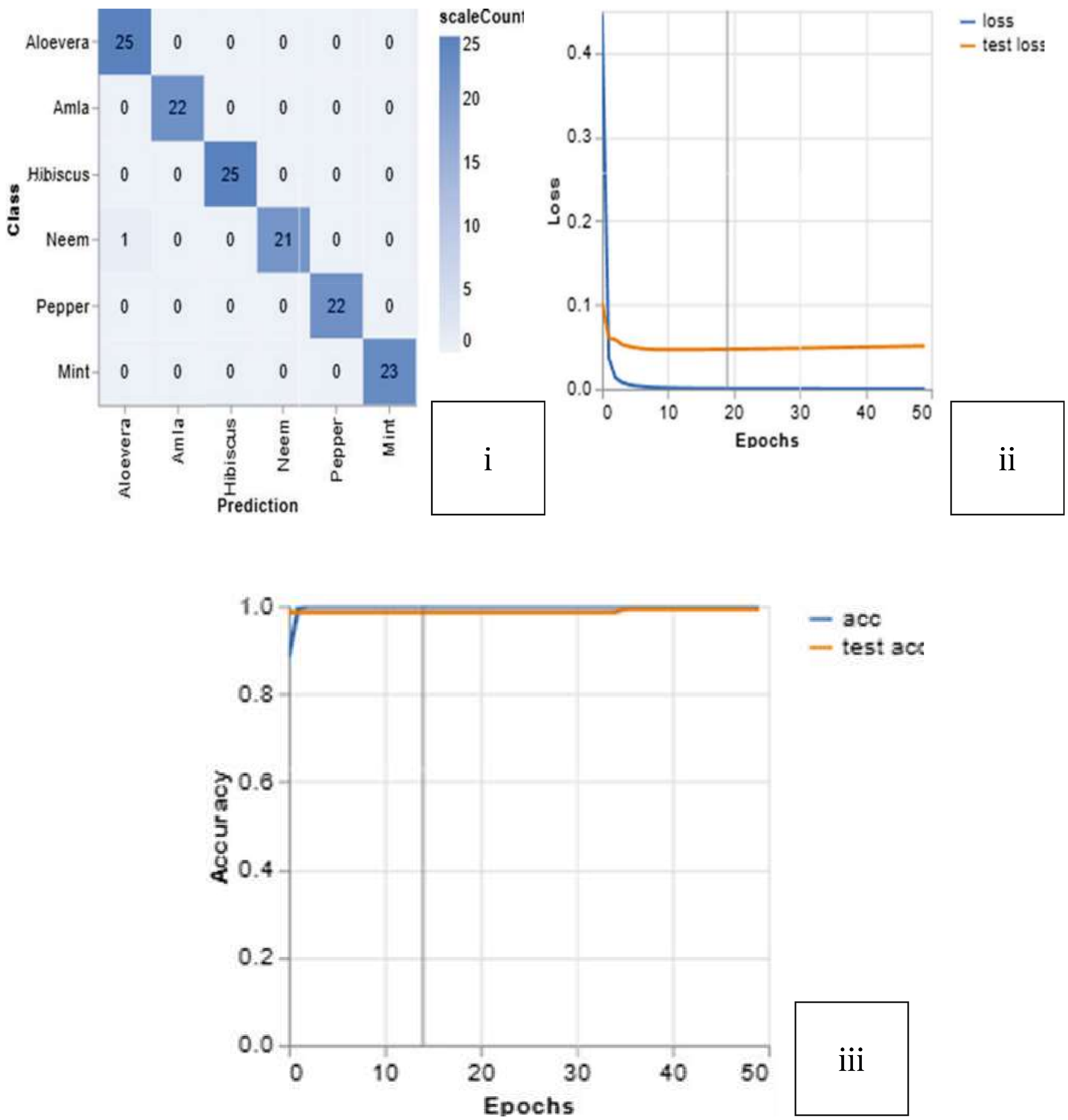

Figure 3: (i) Confusion matrix (ii) Loss per epoch (iii) Accuracy per Epoch

Accuracy per Class

A detailed breakdown of accuracy per class is presented in Table 1, page 112. The results indicate that most plant species achieved an accuracy of 1.00, except for Neem, which exhibited a slightly lower accuracy of 0.95.

The slight decrease in Neem's classification accuracy (Table 1, page 112) may be attributed to variations in morphological features, such as leaf shape and texture, which might have introduced minor inconsistencies in the training process (Wong & Fadzly, 2022, p. 1104). Nevertheless, the overall high classification accuracy across all classes confirms the reliability and robustness of the trained model.

Machine Learning vs. Human Identification in Herbal Plant Recognition

Humans and machines utilize different strategies for plant species identification. While human recognition relies on evolved visual perception, machines replicate this cognitive process using artificial neural networks. These contrasting approaches present distinct strengths and weaknesses. A primary limitation of machine learning models, such as Google's Teachable Machine (GTM), is their dependency on training data. The accuracy of these models is directly determined by the quality and

Class	Accuracy
Aloe Vera	1
Amla	1
Hibiscus	1
Neem	0.95
Pepper	1
Mint	1

Table 1: Accuracy per Class

diversity of the images used during training. Hence, their performance may fluctuate with the introduction of new data. Further, without additional algorithms or specific input refinements, machine learning models can face challenges in adapting to real-world variations (Wong & Fadzly, 2022, p. 1109). One of the key constraints of GTM is its requirement for extensive and diverse datasets to ensure optimal accuracy (Malahina et al., 2024, p. 532). Nonetheless, GTM offers significant advantages in terms of efficiency when handling large datasets. Training traditional machine learning models on local hardware typically requires substantial computational power, particularly for deep learning applications. While high-performance GPUs can mitigate these resource demands, they come at an added cost. GTM addresses this issue by utilizing cloud-based virtual machines, enabling rapid and resource-efficient model training without the need for advanced hardware. This cloud-based system allows users to train models quickly, free of charge, and with minimal computational strain (Wong & Fadzly, 2022, p. 1109).

Previous research (Wong & Fadzly, 2022, p. 1107) has emphasized the role of deep learning in managing large datasets, effectively overcoming some of the challenges faced in plant identification studies. Unlike human experts, who may experience fatigue when manually analyzing numerous plant samples, machine learning models can swiftly and accurately process vast amounts of data. As computational advancements continue, well-trained models will be capable of identifying, classifying, and sorting plant species almost instantaneously. Furthermore, once a model is trained, it remains reliable over time, provided that the morphological traits of the plant species remain consistent. An additional benefit is the ease of sharing trained models with other researchers, promoting faster and more efficient plant identification in scientific studies.

Conclusion

The present study highlights the effectiveness of Google's Teachable Machine (GTM) as a codeless deep learning tool for herbal plant identification. By utilizing convolutional neural networks (CNNs), GTM demonstrated high accuracy in classifying plant species, emphasizing the importance of well-structured training datasets. Factors such as consistent backgrounds, image quality, and adequate lighting played a crucial role in achieving reliable predictions. The study further underscores the advantages of machine learning models over traditional human-based identification, particularly in terms of speed, scalability, and efficiency in handling large datasets. Despite its advantages, GTM has inherent limitations, primarily its reliance on predefined training data. The model's accuracy is contingent upon the diversity and quality of input images, making it less adaptable to real-world variations without additional refinements. Nevertheless, the cloud-based training environment of GTM provides a cost-effective and accessible solution for researchers, eliminating the need for high-performance computing resources. As artificial intelligence continues to evolve, integrating deep learning models into botanical research can significantly enhance species classification, reduce manual workload, and improve data processing efficiency. Future research should explore the integration of more diverse datasets and hybrid approaches to further refine plant identification accuracy. By leveraging such advancements, machine learning can become an indispensable tool for scientific studies in plant taxonomy and biodiversity assessment.

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