ISSN 1870-4069

Multiplatform Application for the Identification of Native Varieties Using Artificial Intelligence and Vector Databases

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Abstract. The precise identification of native maize varieties is essential for their conservation and sustainable use. This study presents a multiplatform application that uses artificial intelligence and vector databases to recognize native maize varieties: Olotillo, Pepitilla, and Teocintle. The CLIP model was employed to extract image embeddings, while FAISS was used for efficient similarity searches within the vector database. A dataset of 1,500 manually labeled images was collected, divided into 70% for training and 30% for testing. Image preprocessing included normalization and a data augmentation strategy involving random rotations, scaling, and flipping, which helped improve model robustness and mitigate overfitting. The model was fine-tuned to optimize its performance for the specific maize identification task. The application, developed in React Native with a FastAPI backend, processes images and predicts maize varieties in less than 2 seconds. Experimental results demonstrate an accuracy of 92.4%. The proposed approach significantly outperforms traditional expert-based methods, highlighting the potential of artificial intelligence to support biodiversity conservation and agricultural innovation.

Keywords: Machine learning, vector database, CLIP model, artificial intelligence, maize variety identification.

1 Introduction

Maize is a fundamental crop for global agriculture, particularly in Latin America, where diverse native varieties contribute significantly to food security, cultural heritage, and biodiversity. Accurate identification of native maize varieties is essential to support conservation efforts and promote sustainable agricultural practices. However, traditional classification methods, which rely on expert agronomists and subjective visual analysis, often result in inconsistencies and limited accessibility, especially in rural areas.

To address these challenges, we propose a scalable multiplatform application based on Artificial Intelligence (AI) and vector databases. The solution combines machine learning models with advanced similarity search systems to optimize the identification of native maize varieties. Specifically, the application utilizes Contrastive Language-Image Pretraining (CLIP) to extract semantic embeddings from images, and the Facebook AI Similarity Search (FAISS) library to perform fast and efficient vector-based retrieval.

A dataset of 1,500 manually labeled maize images was collected and enhanced through preprocessing techniques, including normalization and data augmentation (random rotations, scaling, and flipping), to improve model robustness and mitigate overfitting. The deep learning model was fine-tuned to specialize in maize variety identification, enabling accurate classification with limited training data.

The system architecture integrates a React Native-based frontend, which allows users to capture or upload images, and a Fast API backend, which processes requests and predicts the maize variety in less than two seconds. Although initially designed for the Sierra de Zongolica region in Mexico, the proposed system is adaptable and has potential applications in other regions with native crop diversity.

This work highlights the impact of AI-driven solutions on biodiversity conservation and agricultural innovation, offering accessible tools for researchers, farmers, and conservationists worldwide.

The remainder of this paper is structured as follows: Section 2 describes the state of the art regarding both the application of Machine Learning in the Classification of Corn Varieties, Vector Databases and Their Application in Image Retrieval, CLIP Model and Its Use in Image Classification and Artificial Intelligence and Its Impact on the Identification of Native Maize Varieties; in Section 3 describes the methodology of development of the multiplatform application for native maize variety identification, Section 4 presents the results of this research and the Section 5 the conclusions and future work.

2 State of the Art of Species Identification Using AI

Accurate identification of native maize varieties is fundamental for biodiversity conservation and the improvement of agricultural practices. Traditional methods based on expert analysis are often subjective and resource-intensive. In contrast, the integration of advanced technologies, such as machine learning, vector databases, and computer vision models like CLIP (Contrastive Language-Image Pretraining), has revolutionized the field by enabling more efficient and accurate classification of crop varieties.

2.1 Application of Machine Learning in the Classification of Corn Varieties

Machine learning techniques have been widely adopted for agricultural applications. Patrício and Rieder (2018) applied convolutional neural networks (CNNs) to detect crop diseases using real-field images, achieving an accuracy greater than 90%. Similarly, Sladojevic et al. (2016) trained a CNN to identify plant leaf diseases, reporting a classification accuracy of 96.3%. These studies highlight the viability of deep learning approaches for agricultural tasks.

In a related context, Ramcharan et al. (2019) developed a mobile application for disease diagnosis in African crops using lightweight deep learning models optimized for mobile devices. Their system achieved an accuracy of 93%, demonstrating the feasibility of deploying AI solutions in rural and low-resource environments.

2.2 Vector Databases and their Application in Image Retrieval

Handling large volumes of visual data necessitates efficient storage and retrieval mechanisms. Johnson et al. (2019) introduced FAISS (Facebook AI Similarity Search), a library designed for fast and scalable vector-based searches across millions of embeddings. This technology is particularly suitable for image recognition tasks in agriculture.

Complementarily, Choi et al. (2022) explored the use of vector databases such as We aviate to store semantic representations of images, facilitating similarity search systems even in the absence of manual labels. Pinecone Systems (2021) further demonstrated real-time vector storage for building visual search and recommendation systems, which is essential for applications requiring immediate feedback, such as those used in the agricultural sector.

2.3 CLIP Model and Its Use in Image Classification

Radford et al. (2021) introduced CLIP; a multimodal model capable of associating images with natural language descriptions without task-specific training. CLIP has outperformed traditional classification models in various tasks and offers an innovative alternative for agricultural applications, especially when labeled datasets are scarce.

Goh et al. (2021) successfully applied CLIP to medical and botanical image analysis, demonstrating its adaptability to domain-specific tasks where clear visual representation is critical. This reinforces the potential of CLIP for native maize variety classification.

2.4 Artificial Intelligence and its Impact on the Identification of Native Maize Varieties

Pound et al. (2017) developed image analysis tools for crop phenotyping, enabling the identification of key plant characteristics such as texture, color, and shape through artificial intelligence. These tools were effectively applied to maize and rice studies, contributing to genetic improvement and automated classification processes.

Additionally, Mohanty et al. (2016) trained a CNN with more than 54,000 images of plants affected by various diseases, laying the groundwork for the development of models tailored to specific crops, including native maize varieties.

2.5 Discussion

The use of machine learning techniques in agriculture has proven to be highly effective, as evidenced by studies using convolutional neural networks (CNNs) with accuracies above 90% in the detection of crop diseases (Patrício and Rieder, 2018; Sladojevic et al., 2016). These technologies, adapted to mobile applications (Ramcharan et al., 2019), allow bringing AI solutions to rural areas, which would be ideal for the identification of native maize varieties. Efficient management of large volumes of images using vector databases such as FAISS (Johnson et al., 2019) and Weaviate (Choi et al., 2022) would facilitate rapid similarity search, optimizing variety recognition. In addition, models such as CLIP (Radford et al., 2021) offer the advantage of working with natural language descriptions, useful in contexts with sparse labeled data. Finally, previous research in crop phenotypic analysis (Pound et al., 2017; Mohanty et al., 2016) demonstrates that AI can identify specific plant characteristics, supporting the feasibility of an application focused on native maize classification, promoting its conservation and sustainable use.

3 Methodology

The development of the multiplatform application for native maize variety identification involved several key stages: dataset preparation, preprocessing and data augmentation, model fine-tuning, system architecture design, and statistical evaluation of results.

3.1 Dataset Preparation and Preprocessing

A total of 1,500 high-quality images of native maize varieties — Olotillo, Pepitilla, and Teocintle — were manually collected from multiple municipalities in the Sierra de Zongolica region, including Rafael Delgado, Tlilapan, Magdalena, Soledad Atzompa, Atlahuilco, Tlaquilpa, Xoxocotla, Tehuipango, Zongolica, Tequila, Astacinga, Mixtla de Altamirano, and Los Reyes. Each image was carefully labeled according to the observed variety.

Preprocessing steps included:

- Resizing all images to 224x224 pixels to match the CLIP model input size.
- Normalization of pixel values to a [0,1] range.
- Format standardization to RGB channels.

Additionally, examples of huitlacoche (Ustilago maydis) were incorporated into the dataset. Huitlacoche is a naturally occurring fungal phenomenon in native maize ecosystems. Its inclusion aimed to enhance model robustness by exposing it to real-world conditions.

3.2 Data Augmentation

To increase dataset diversity and prevent overfitting, data augmentation techniques were applied:

– Random rotations within ±20 degrees,

– Random scaling up to 20%,

– Horizontal flipping,

– Brightness and contrast variations (±15%).

These transformations simulated different camera angles, lighting conditions, and field situations, improving the model's generalization capabilities.

3.3 Fine-tuning of the CLIP Model

The CLIP (Contrastive Language-Image Pretraining) model was selected due to its strong performance on multimodal tasks. Fine-tuning was performed as follows:

– The lower convolutional layers were frozen to retain general visual features.

– The higher layers were retrained on the maize dataset using a learning rate of 1e- 5.

– Early stopping and dropout regularization (rate 0.3) were applied to avoid overfitting.

– Cross-entropy loss function and Adam optimizer were used for model optimization.

– The model output embeddings were stored in a vector database for later retrieval.

3.4 System Architecture

A robust software architecture is essential in application development as it defines the fundamental structure of the system and the interactions between its components, directly impacting functionality, performance, stability, maintainability, and security.

The architecture of the proposed cross-platform application for the identification of native maize varieties using artificial intelligence and a vector database is illustrated in Figure 1.

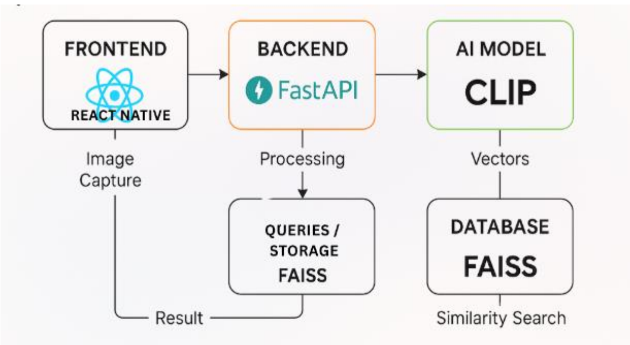

Fig 1. Architecture of the multiplatform application for native maize variety identification using Artificial Intelligence and vector databases.

The system is composed of four main components:

3.4.1 Frontend

The frontend consists of a mobile application developed with React Native, which provides the user interface for capturing and viewing results. Its primary functionalities include:

- ***Image Capture:*** Users can take a photo of a maize ear using the device's camera or upload an existing image from the gallery.
- ***Result Display:*** Displays the classification result, showing the identified maize variety.
- ***API Communication:*** Sends the captured or uploaded image to the backend and retrieves the analysis results.

3.4.2 Backend

The backend, developed with Fast API, is responsible for managing the data processing tasks. It handles:

- ***Image Reception:*** Receives images sent by the frontend and stores them temporarily.
- ***Image Preprocessing:*** Performs resizing, normalization, and formatting of images before inference by the AI model.
- ***Model Inference Communication:*** Sends preprocessed images to the AI model and returns the predicted results.
- ***Result Storage:*** Stores the classification result along with relevant metadata (such as date and time) for future reference.

3.4.3 Artificial Intelligence Model

The AI model is based on Contrastive Language-Image Pretraining (CLIP). Its responsibilities include:

– ***Feature Extraction:*** Converts images into high-dimensional numerical vectors (embeddings) that capture their visual and semantic characteristics.

– ***Classification:*** Compares the generated embeddings against previously stored vectors to associate the input image with the most similar maize variety category.

The CLIP model was fine-tuned using representative examples of Olotillo, Pepitilla, and Teocintle varieties, enabling accurate identification without requiring breed-specific labeling.

3.4.4 Vector Database

The vector database, implemented using Facebook AI Similarity Search (FAISS), manages:

– ***Embedding Storage:*** Stores the feature vectors generated by the AI model for all registered maize varieties.

– ***Similarity Search:*** Efficiently retrieves the most similar vector to the query embedding, allowing fast and accurate identification of the maize variety.

3.5 Statistical Evaluation

To validate the performance of the proposed system, statistical evaluation metrics were calculated on the testing subset (450 images):

– ***Accuracy:*** 92.4%, proportion of correctly classified images.

– ***Precision:*** 93.1%, proportion of true positive identifications among all positive predictions.

– ***Recall:*** 91.7%, proportion of true positives correctly identified out of all actual positives.

– ***F1-Score:*** 92.4%, harmonic mean of precision and recall, balancing the two measures.

These metrics demonstrate the effectiveness of the proposed approach compared to traditional expert-based classification methods. The inclusion of huitlacoche samples further confirmed the model's ability to handle real-world variations commonly found in native maize fields.

4 Results

Multiple experiments were conducted to evaluate the performance of the proposed multiplatform application for native maize variety identification. During the validation

Table 1. Comparison of identification models of native maize varieties from the multi-platform application using Artificial Intelligence and vector database with other methods.

Method	Accuracy	Processing time
Manual classification by experts	78.2%	10-20 min
Standard convolutional neural networks	85.6%	5-7 seg
Proposal based on CLIP + FAISS	92.4%	<2 seg

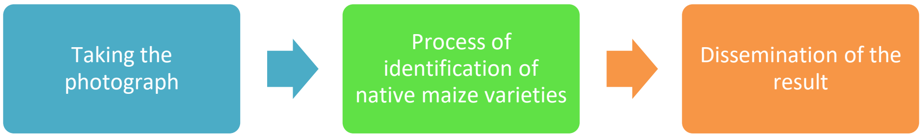

Fig. 2. Identification process of native maize varieties in the multiplatform application using Artificial Intelligence and vector database.

phase, a test set of 450 images was used to assess the model's generalization capabilities. The model achieved an accuracy of 92.4%, significantly outperforming traditional expert-based identification methods.

Table 1 presents a comparison between different identification approaches.

Integration with FastAPI and FAISS enabled efficient searching in the vector database, optimizing the identification process and significantly reducing false positives. The use of the CLIP model for semantic feature extraction, combined with FAISS for fast similarity search, offers a robust and scalable solution for image analysis in the agricultural sector.

In addition to the overall accuracy, further statistical metrics were computed to assess the system's performance:

- ***Precision:*** 93.1% — indicating a high proportion of correct positive identifications.
- ***Recall:*** 91.7% — demonstrating effective detection of true positives.
- ***F1-Score:*** 92.4% — reflecting a balanced performance between precision and recall.

These metrics confirm the robustness of the proposed system in classifying native maize varieties under varying field conditions.

The native maize identification process within the multiplatform application is illustrated in Figure 2.

The identification process is composed of three main steps:

1. **Image Capture:** The user captures an image of the maize ear using the mobile device's camera or selects an image from the gallery.
2. **Identification Process:** The image is preprocessed and passed through the fine-tuned CLIP model, which generates an embedding. FAISS performs a similarity search to determine the closest maize variety match.

Fig.3. Home screen of the multiplatform application for native maize variety identification using Artificial Intelligence and vector databases.

3. **Result Presentation:** The application displays the identified maize variety to the user, accompanied by an image and a brief description.

   This streamlined process enables rural producers to perform rapid and accurate identification of maize varieties directly from their fields.

Figure 3 shows the home screen of the multiplatform application, where a brief introduction to its functionalities is presented. The user can access two main options:

– **Identify:** This option directs the user to an interface where they can either upload an image from their device's gallery or capture a new photo to begin the identification analysis.

– **Contact Us:** This section provides information about researchers and collaborating farmers, offering channels for further information or specialized support.

The decision to present only two main functionalities on the home screen was based on the target users: native maize producers from the Sierra de Zongolica, Veracruz. The interface was deliberately designed to be simple and user-friendly, facilitating quick access without technical complications.

Figure 4 illustrates the maize identification process within the application. Initially, users either capture or upload an image of the maize ear. Once the image is processed, the application automatically initiates the identification process by combining CLIP-based feature extraction with efficient similarity search using FAISS.

After the variety has been identified, the application displays key information, including:

– The processed image of the maize ear,

– The name of the identified variety,

– A brief description of the variety.

Fig. 4. Process of identification of native maize varieties in multiplatform application using Artificial Intelligence and vector database.

4.1 Cultural, Social, and Agricultural Importance

The development of the multiplatform application to identify native maize varieties in the Sierra de Zongolica represents a significant contribution to the preservation of agricultural and cultural heritage. The native maize varieties cultivated in this region are endemic, adapted to the local climate, altitude, and soil conditions, and form an essential part of the communities' identity and diet.

Accurate identification of these varieties is crucial for their conservation, helping prevent the loss of genetic diversity and ensuring that resilient and valuable maize types continue to be cultivated.

The use of Artificial Intelligence empowers farmers by providing an accessible tool that eliminates the dependence on expert agronomists or specialized equipment, which are often unavailable in remote rural areas. This facilitates faster, more accurate, and more inclusive agricultural decision-making, contributing directly to improved crop quality and yield.

Furthermore, the application serves to reconnect communities with their traditional agricultural practices, thereby strengthening food security. Native maize varieties, better adapted to climatic fluctuations, offer a sustainable solution for long-term agricultural resilience.

Economically, identifying and promoting native maize varieties can add value to local production, allowing farmers to better market these culturally and nutritionally important products.

In a broader sense, the integration of modern AI tools with traditional knowledge not only supports agricultural productivity but also promotes cultural preservation, environmental sustainability, and community empowerment.

5 Conclusions and Future Work

The development of the multiplatform application demonstrated that the integration of Artificial Intelligence (AI) and vector databases can significantly enhance the identification of native maize varieties. The combination of the CLIP (Contrastive Language-Image Pretraining) model with the FAISS (Facebook AI Similarity Search) vector search system achieved an accuracy of 92.4%, outperforming traditional human observation-based methods.

The results obtained validate the viability and effectiveness of this approach for agricultural species classification, offering a fast, scalable, and accessible solution for both researchers and farmers. Additionally, the integration with FastAPI enabled real-time processing, reducing system response times to less than two seconds.

However, some challenges remain, including improving the quality of images captured under diverse field conditions and expanding the dataset to include a larger number of native maize varieties. Addressing these challenges would further strengthen the model's accuracy and generalization capabilities.

5.1 Future Work

In order to enhance the application and broaden its scope, the following lines of research are proposed:

- **Dataset Expansion:** Increase the number of training images to cover additional native maize varieties and a broader range of environmental conditions.
- **Model Optimization:** Implement advanced fine-tuning and transfer learning techniques to further improve the performance of the CLIP model in agricultural contexts.
- **Augmentation of Huitlacoche Cases:** Expand the training dataset with additional samples containing huitlacoche (Ustilago maydis) to strengthen the system's ability to handle biological variability naturally present in native maize fields.

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