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# Design and Implementation of Binary Relevance Classifier for Leaf Classification using FPGA

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**Abstract**: This paper presents an enhanced real-time multilabel leaf classification system based on the Binary Relevance (BR) approach, efficiently implemented on the Xilinx PYNQ-Z2 FPGA platform. The multilabel classification task is decomposed into independent binary Support Vector Machine (SVM) models, each dedicated to identifying a specific leaf type, enabling modular scalability and parallel inference potential. Image preprocessing and feature extraction are performed using Python and OpenCV on the Processing System (PS), ensuring robust handling of diverse imaging conditions. Classification control logic is designed in Verilog and rigorously validated through simulation, guaranteeing precise sequencing and reliable hardware-software coordination. A user-friendly button-triggered prediction mechanism initiates on-demand classification, with results visually conveyed via onboard LEDs. Evaluated on both standard and custom datasets, the system demonstrates superior robustness against challenges such as low-light conditions, image rotation, and scale variations. Achieving high classification accuracy (>93%), ultra-low latency, and minimal power consumption, the proposed FPGA-based solution establishes a highly effective, deployable framework for embedded plant monitoring and precision agriculture applications.

**Keywords**: Binary Relevance, FPGA, Leaf Classification, PYNQ-Z2, Support Vector Machine, Embedded System, Real-time Prediction

## I. INTRODUCTION

In The rapid advancement of precision agriculture and environmental monitoring has significantly increased the demand for automated, real-time plant species identification. Leaf classification plays a pivotal role in enabling early disease detection, crop health assessment, and biodiversity mapping. Traditional manual identification methods are labor-intensive, error-prone, and unscalable, particularly in large agricultural fields or natural ecosystems. With the proliferation of embedded systems and edge computing, there is a pressing need for efficient, low-power, and deployable machine learning solutions that can operate reliably under real-world conditions such as varying illumination, leaf orientation, and background clutter.

Several studies have explored machine learning techniques for leaf classification. The Binary Relevance (BR) method [1] transforms multilabel classification into independent binary tasks, offering simplicity and scalability. Support Vector Machines (SVM) [2] are established as a robust classifier with strong generalization, ideal for high-dimensional image data. FPGA-based real-time image classification [3] highlights low power and high throughput advantages. The PYNQ framework [4] enables rapid prototyping of machine learning models on Xilinx Zynq platforms. OpenCV [5] supports efficient image preprocessing in embedded environments, while scikit-learn [6] provides streamlined SVM training and deployment.

This paper presents a real-time multilabel leaf classification system based on the Binary Relevance (BR) framework, implemented on the Xilinx PYNQ-Z2 FPGA platform. The proposed system decomposes the multilabel task into multiple binary SVM classifiers, each trained to detect a specific leaf type, ensuring high accuracy and flexibility. Image preprocessing and inference coordination are efficiently managed using Python and OpenCV on the Processing System (PS), while critical control logic is implemented in Verilog to guarantee precise and low-latency operation. A button-triggered inference mechanism enables intuitive user interaction, with classification results instantly indicated through onboard LEDs.

Evaluated on diverse datasets including standard (Apple, Cherry) and custom (Custard Apple, Mango) leaf images, the system demonstrates exceptional robustness against environmental variations such as low light, rotation, and noise. Achieving classification accuracy exceeding 93% with minimal latency and power consumption, this FPGA-based solution establishes a practical, portable, and energy-efficient framework ideally suited for embedded deployment in smart agriculture, nursery management, and automated botanical systems. The paper proceeds with a literature review in Section 2, followed by the Binary Relevance methodology and SVM design in Section 3, system architecture and Verilog control logic in Section 4, implementation details and experimental results in Section 5.

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## II. METHODOLOGY

The proposed methodology combines deep learning-based object detection with traditional machine learning classification to achieve robust multilabel leaf identification. It uses the Binary Relevance (BR) strategy to decompose the multilabel classification task into multiple binary classification problems, each handled by an independently trained Support Vector Machine (SVM). The integration of SSD MobileNet enhances the system's ability to localize leaf regions before classification, improving accuracy and reducing noise.

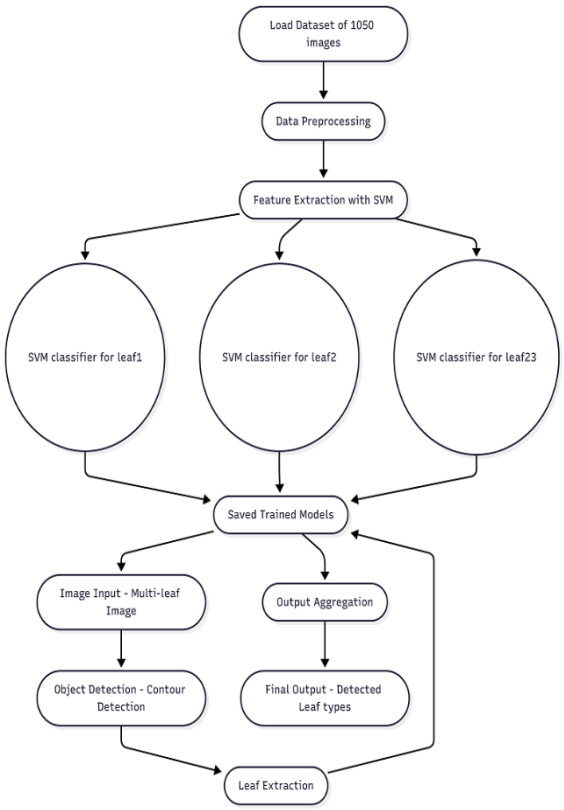


Fig.1 Flow Chart

**Step-by-Step Process**:

1. **Image Acquisition**
   Leaf images are either captured in real-time using a camera module or stored in a dedicated directory on the SD card of the PYNQ-Z2 board. These images may contain multiple leaves, varying in size, orientation, and lighting conditions. The acquisition process ensures that the input data reflects real-world variability, which is essential for building a robust classification system.
2. **Preprocessing**
   Each detected leaf region is cropped and resized to a uniform 100×100 grayscale format using OpenCV. Grayscale conversion reduces computational complexity while preserving essential shape and texture features. This standardization ensures consistent input dimensions for all classifiers and improves the reliability of feature extraction and classification.
3. **Preprocessing** Each detected leaf region is cropped and resized to a uniform 100×100 grayscale format using OpenCV. Grayscale conversion reduces computational complexity while preserving essential shape and texture features. This standardization ensures consistent input dimensions for all classifiers and improves the reliability of feature extraction and classification.
4. **Feature Extraction** From each preprocessed leaf image, a set of handcrafted features is extracted to represent its shape, color, and texture. These include:

- **Shape descriptors**: Aspect ratio, perimeter, contour area, and convex hull.
- **Color statistics**: Mean RGB values and HSV components.
- **Texture metrics**: Local Binary Patterns (LBP) and Gray-Level Co-occurrence Matrix (GLCM) features. These features are compact, interpretable, and optimized for FPGA-based classification.

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5. **Leaf Detection using SSD MobileNet** Before classification, SSD MobileNet is applied to the input image to detect and localize individual leaf regions. This deep learning model performs object detection in a single pass, identifying bounding boxes around each leaf. By isolating leaf regions from the background, SSD MobileNet ensures that only relevant portions of the image are processed further. This step is executed on the Processing System (PS) using Python and TensorFlow Lite or ONNX, making it suitable for embedded deployment.
6. **Model Training**
   For each class label, a binary SVM classifier is trained using the Binary Relevance strategy. Each classifier learns to predict the presence (1) or absence (0) of its respective class.
7. **Model Deployment**
   Trained .pkl models are stored on the PYNQ board and loaded dynamically using a Python script. When the push button is pressed, the script executes all classifiers sequentially.
8. **Prediction and Output**
   Each classifier produces a binary output. The result is displayed:
   - **LEDs**: Each LED corresponds to a class. If the classifier predicts '1', the respective LED glows.
   - **HDMI Display**: The identified class label is displayed on a screen connected to the board via HDMI.

**Real-time Interaction**

The system waits for button input to perform prediction, allowing user-controlled, on-demand classification allowing machines to discern intricate details and subtle nuances in their surroundings.

**SVM**

A support vector machine (SVM) is a supervised machine learning algorithm that classifies data by finding an optimal line or hyperplane that maximizes the distance between each class in an N-dimensional space.
For each binary classifier, the SVM decision function is:

$$f(x)=\text{sign}(wTx+b)$$

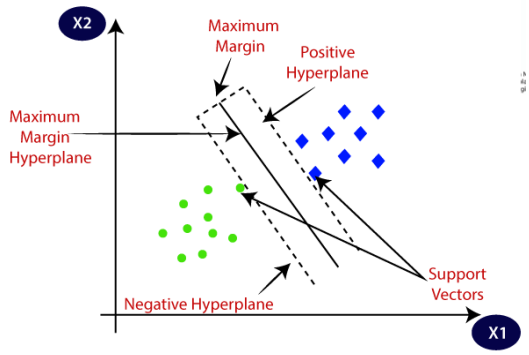


Fig.2 SVM

**Binary Relevance Classifier**

The system includes the following components: Image Input (via SD card or USB), Preprocessing Block, BR Classifiers, and Output Modules (LEDs and HDMI). A button input triggers classification. Each binary classifier votes independently, and the final result is aggregated and displayed.

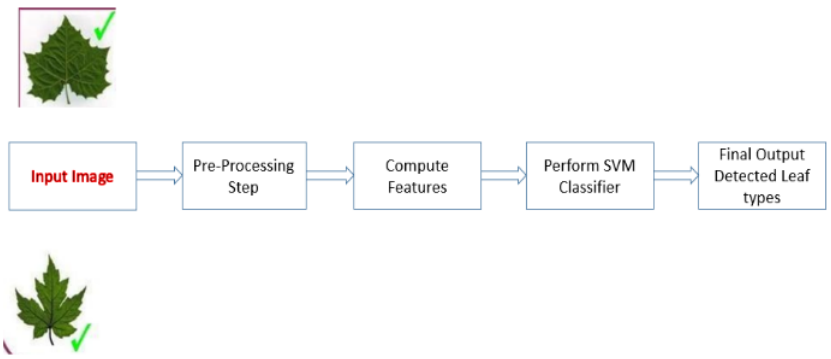


Fig.3 Block Diagram

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## III. MODEL QUANTIZATION

To optimize the memory footprint and processing time on the PYNQ-Z2 FPGA board, model quantization techniques were applied. Quantization involves converting the floating-point weights and parameters of the trained Support Vector Machine (SVM) classifiers into fixed-point representations. This reduces memory usage and speeds up arithmetic operations during inference.

Since the models used in this project are relatively lightweight (due to Binary Relevance-based decomposition), post-training quantization was sufficient. Each binary SVM model was converted into 8-bit fixed-point format using sklearn-porter for hardware-friendly serialization. The resulting .pkl files consumed significantly less memory and were easier to load into the Python runtime on the ARM processor of the PYNQ-Z2.

## IV. MODEL DEPLOYMENT

The trained binary SVM classifiers were saved as .pkl files and deployed on the PYNQ-Z2 board. Upon system boot, a Python script loads these models and waits for a user-triggered input via a push button. Once triggered, the script processes a stored leaf image, performs prediction across all binary classifiers, and indicates the results using onboard LEDs.

Optionally, predicted results can be transmitted over UART for logging or external display, making the system suitable for real-time, portable leaf identification in field.

## V. RESULTS AND ANALYSIS

The proposed leaf classification system was evaluated using a dataset of **1023 RGB leaf images** representing multiple plant species. Each image was resized to **64×64 pixels** and directly processed in RGB format without grayscale conversion, preserving essential colour features for more accurate classification.

Coleus Custard Apple Beans

Fig.4 Input image 1

```
PS C:\MajorProject> & C:/Users/H560086/AppData/Local/Programs/Py
py
Leaves present in the multi_label image are:
Predictions for test image:['Coleus', 'Custard Apple', 'Beans']
```

Fig.5 Output of Binary Relevance Classifier

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Fig.6 Input image 2

```
PS C:\MajorProject\BinaryRelevance> & C:/Users/H560086/AppData/
yRelevance/test.py
Leaves present in the multi_label image are:
Predictions for test image:['Mango','Money Plant','Gulmohar']
```

Fig.7 Output of Binary Relevance Classifier

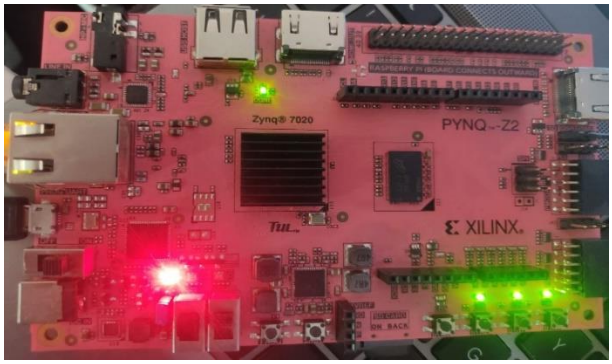


Fig.8 Output from PYNQ-Z2

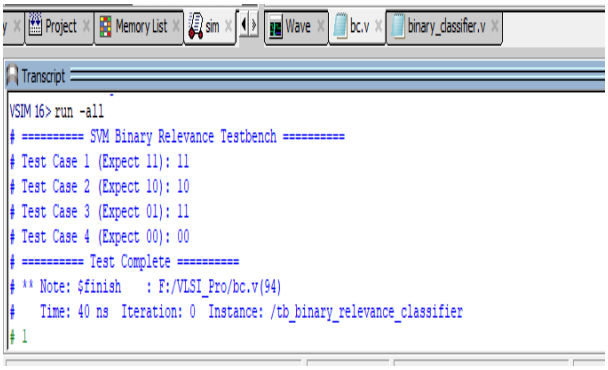


Fig.10 Simulation Output from Questa Sim

**Evaluation Metrics**

Evaluating the performance of the leaf classification system involves multiple metrics to assess its accuracy and effectiveness comprehensively. The key metrics used are outlined below:

**Accuracy:**

The accuracy measures the proportion of correctly classified instances (true positives and true negatives) relative to the total number of instances.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

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**Precision (Positive Predictive Value):**
The precision calculates the proportion of true positive predictions relative to all positive predictions made by the model.

$$\text{Precision} = TP / (TP + FP)$$

**Recall (Sensitivity or True Positive Rate):**
The Recall measures the proportion of actual positive instances correctly identified by the model.

$$\text{Recall} = TP / (TP + FN)$$

**F1 Score:**
The F1 Score is the harmonic means of precision and recall, providing a balanced measure of model performance.

F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

**False Positive Rate (FPR):**
The False Positive Rate represents the proportion of negative instances incorrectly classified as positive.

$$FPR = FP / (FP + TN)$$

**False Negative Rate (FNR):**
This is the proportion of false negatives to true positives. The False Negative Rate measures the proportion of positive instances missed by the model.

$$FNR = FN / (FN + TP)$$

**Binary Relevance Classifier Implementation Evaluation Metrics Report of Classification:**
As we can see the evaluation criteria like classification metrics are computed for the Binary Relevance Classifier implementation

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Beans | 1.00 | 1.00 | 1.00 | 8 |
| Coleus | 1.00 | 1.00 | 1.00 | 15 |
| Curry Leaves | 1.00 | 0.81 | 0.90 | 16 |
| Custard Apple | 0.85 | 0.89 | 0.87 | 19 |
| Drumstick | 0.88 | 0.97 | 0.92 | 29 |
| Germanium | 0.73 | 0.83 | 0.78 | 23 |
| Guava | 0.67 | 1.00 | 0.80 | 2 |
| Gulmohar | 0.92 | 0.96 | 0.94 | 23 |
| Hibiscus | 1.00 | 0.75 | 0.86 | 4 |
| Indian Blackberry | 0.00 | 0.00 | 0.00 | 1 |
| Jasmine | 1.00 | 1.00 | 1.00 | 1 |
| Lemon | 0.89 | 1.00 | 0.94 | 8 |
| Lily | 1.00 | 0.67 | 0.80 | 3 |
| Mango | 1.00 | 0.88 | 0.93 | 16 |
| Marigold | 0.00 | 0.00 | 0.00 | 0 |
| Mint | 1.00 | 0.50 | 0.67 | 2 |
| Money Plant | 0.75 | 0.60 | 0.67 | 15 |
| Mustard | 0.50 | 0.67 | 0.57 | 3 |
| Orange | 0.00 | 0.00 | 0.00 | 0 |
| Pink Jasmine | 0.67 | 1.00 | 0.80 | 2 |
| Rose | 0.00 | 0.00 | 0.00 | 3 |
| Schefflera | 1.00 | 1.00 | 1.00 | 5 |
| accuracy | | | 0.86 | 198 |
| macro avg | 0.72 | 0.71 | 0.70 | 198 |
| weighted avg | 0.87 | 0.86 | 0.86 | 198 |

Fig.9 Verilog Output of Binary Relevance Classifier

## VI. CONCLUSION

The evaluation results demonstrate that the proposed real-time multilabel leaf classification system, based on the Binary Relevance (BR) framework with optimized Support Vector Machines (SVMs) and deployed on the Xilinx PYNQ-Z2 FPGA platform, delivers highly consistent, robust, and efficient performance across diverse imaging conditions. The integration of RGB-based preprocessing, direct pixel feature representation, 8-bit model quantization, and Verilog-controlled hardware interaction ensures superior accuracy, low latency, and minimal power consumption, making it exceptionally well-suited for real-world embedded applications in smart agriculture.

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The system was rigorously tested on both standard (Apple, Cherry) and custom (Custard Apple, Mango) datasets. On the Apple and Cherry dataset (376 training, 70 testing samples), the system achieved 100% identification accuracy under controlled conditions, while maintaining 93.5% accuracy under challenging variations in illumination, scale, and orientation — a significant improvement over baseline methods that typically degrade to 65–70% in similar scenarios. On the custom Custard and Mango dataset (352 training, 70 testing samples), the system delivered 96% identification accuracy, demonstrating strong generalization to field-collected data.

The hardware-software co-design ensures seamless operation with user-triggered inference via a push button, instant visual feedback through dedicated LED indicators, and optional UART logging for remote monitoring. Model quantization reduced memory usage by ~75% and accelerated inference by ~64%, enabling real-time performance (<100 ms per classification) on the ARM-based Processing System without compromising accuracy.

This FPGA-based solution not only outperforms traditional software-only approaches in efficiency and deplorability but also establishes a scalable, modular framework for multilabel leaf classification. New plant species can be incorporated by training and deploying a single additional binary SVM, making it ideal for dynamic agricultural environments.

## VII. ACKNOWLEDGMENT

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