PRECISION AGRICULTURE IN VITICULTURE: GRAPE DISEASE DETECTION USING GLCM AND MULTI-CLASS SVM

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Abstract :* Precision agriculture has emerged as a transformative approach in viticulture, enabling early disease detection and effective vineyard management. This study focuses on the automated detection and classification of grapevine diseases using Gray-Level Co-Occurrence Matrix (GLCM) for texture feature extraction and Multi-Class Support Vector Machine (SVM) for classification. GLCM, a widely used texture analysis method, captures spatial relationships between pixel intensities, allowing for the identification of disease-specific patterns in grape leaves. The extracted features, including contrast, correlation, energy, and homogeneity, are then fed into a Multi-Class SVM model to classify various grape diseases such as powdery mildew, downy mildew, black rot, and healthy leaves. The proposed model is trained and validated on a dataset of grape leaf images, achieving high classification accuracy. By leveraging machine learning and image processing techniques, this approach provides an efficient and cost-effective solution for disease monitoring in vineyards, reducing the reliance on manual inspections and chemical treatments. The integration of such automated disease detection systems into precision agriculture frameworks can significantly enhance crop health management, improve yield quality, and promote sustainable viticulture practices.

***Index Terms* - Precision Agriculture, Viticulture, Grape Disease Detection, Gray-Level Co-Occurrence Matrix, Multi-Class Support Vector Machine, Texture Analysis, Machine Learning, Image Processing**

1. INTRODUCTION

Viticulture, the cultivation of grapevines, plays a crucial role in the global agricultural economy, particularly in wine production and fresh fruit markets [1]. However, grapevines are highly susceptible to various fungal, bacterial, and viral diseases that significantly impact crop yield and quality. Among the most common grape diseases are powdery mildew, downy mildew, and black rot, which can spread rapidly if not detected and managed in time. Traditional disease detection methods rely on manual inspection by farmers and agronomists, which are labour-intensive, time-consuming, and prone to human error. Moreover, late detection often leads to excessive use of chemical fungicides, negatively affecting both the environment and the quality of the produce [2].

To address these challenges, the integration of precision agriculture techniques with advanced computational methods offers a promising solution. In recent years, machine learning and image processing have gained significant attention for automating plant disease detection [3]. Texture analysis plays a vital role in identifying disease-specific patterns in grape leaves, as many diseases exhibit distinct texture variations. The Gray-Level Co-Occurrence Matrix (GLCM) is a well-established texture analysis method that extracts features such as contrast, correlation, energy, and homogeneity, enabling the differentiation of healthy and diseased leaves. These extracted features can be effectively used as input for machine learning classifiers to achieve accurate disease classification [4].

In this study, we propose an automated grape disease detection framework using GLCM for texture feature extraction and a Multi-Class Support Vector Machine (SVM) [5] for classification. Multi-Class SVM is a robust supervised learning algorithm that efficiently classifies multiple disease categories based on extracted features. The objective is to develop a reliable, non-invasive, and cost-effective disease detection system that can assist viticulturists in early disease identification and management. By implementing such a system, farmers can optimize pesticide usage, minimize economic losses, and improve vineyard productivity while promoting sustainable farming practices.

Objectives of the Paper

1. **To develop an automated grape disease detection framework** using Gray-Level Co-Occurrence Matrix (GLCM) for texture feature extraction and Multi-Class Support Vector Machine (SVM) for classification.
2. **To analyze the texture-based feature variations** between healthy and diseased grape leaves using statistical measures such as contrast, correlation, energy, and homogeneity.
3. **To evaluate the classification performance** of multi-Class SVM in identifying different grapevine diseases, including powdery mildew, downy mildew, and black rot.
4. **To provide an efficient and cost-effective solution** for disease monitoring in vineyards, reducing the dependency on manual inspections and excessive chemical treatments.

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2. LITERATURE SURVEY

K. Tyagi, A. Karmarkar, S. Kaur, S. Kulkarni, and R. Das [4] developed a crop health monitoring system to assist farmers in identifying diseases on crop leaves and preventing their spread. The system continuously collects data on environmental parameters such as temperature, humidity, soil moisture, and rainfall using field sensors. If unfavorable conditions are detected, registered farmers receive alerts. Additionally, farmers can upload images of affected plants via a web or Android application for disease identification, enabling timely intervention.

V. Pallagani, V. Khandelwal, B. Chandra, V. Udutalapally, D. Das, and S. P. Mohanty [5] emphasize the growing global population's impact on food demand and highlight crop diseases as a major threat to food security.

P. Shankar, A. Johnen, and M. Liwicki 16] investigate the integration of data fusion with artificial neural networks (ANN) for predicting Septoria Tritici, a severe disease in winter wheat. Their study highlights the complexity of adapting disease models to climate change and the importance of advanced decision-support systems in agricultural disease management.

D. Long, H. Yan, H. Hu, P. Yu, and D. Hei [7] propose video monitoring for crop disease detection in greenhouses. The Haar-Adaboost algorithm is used to identify relevant crop images, discarding irrelevant ones, ensuring accurate pest and disease detection.

D. Radovanović and S. Đukanovic [8] stress the need for early disease detection due to the increasing global food demand. They highlight the limitations of traditional methods, such as cost and inaccessibility in rural areas, and explore the potential of deep learning-based automated image analysis as a more efficient alternative to traditional machine learning techniques.

R. Setiawan, H. Zein, R. A. Azdy, and S. Sulistyowati [9] explore the use of the Nu-Support Vector Machine (Nu-SVM) for classifying rice leaf diseases, specifically BrownSpot and LeafBlast. Using a dataset processed with Sobel edge detection and Hu Moments feature extraction, their study achieved moderate accuracy (52.12%–53.81%) across 5-fold cross-validation. The findings underscore the need for advanced image processing and feature extraction techniques to improve disease detection models, contributing to precision agriculture and sustainable farming practices.

3. RESEARCH METHODOLOGY

Algorithm 1 Image Classification with SVM

```
Input: data_dir, categories, img_size
Output: Classification metrics and plots
Initialize empty lists data and labels
total_images ← ∑ number of images in each category
processed_images ← 0
for category in categories do
    path ← concatenate data_dir and category
    label ← index of category in categories
    images ← list of images in path
    for img in images do
        img_path ← concatenate path and img
        img_array ← read image from img_path
        if img_array ≠ None then
            img_array ← resize img_array to img_size
            append img_array to data
            append label to labels
        end if
        processed_images ← processed_images + 1
        percentage ← (processed_images / total_images) × 100
        print Processing percentage
    end for
end for
Convert data and labels to numpy arrays
train_data, test_data, train_labels, test_labels ←
    train_test_split(data, labels, test_size = 0.2, random_state = 42)
train_data_flat ← reshape train_data to 2D
test_data_flat ← reshape test_data to 2D
Initialize SVM model svm_model with kernel =' linear' and C = 1
Train svm_model on train_data_flat and train_labels
predictions ← svm_model.predict(test_data_flat)
accuracy ← accuracy_score(test_labels, predictions)
print Accuracy
print Classification Report
Compute precision, recall, f1_score per class
Plot precision, recall, f1_score per class and overall accuracy
```

Algorithm 1 Image Classification with Decision Tree

```
Input: data_dir, categories, img_size
Output: Classification metrics and plots
Initialize empty lists data and labels
for category in categories do
  path ← concatenate data_dir and category
  label ← index of category in categories
  images ← list of images in path
  for img in images do
    img_path ← concatenate path and img
    img_array ← read image from img_path
    if img_array ≠ None then
      img_array ← resize img_array to img_size
      append img_array to data
      append label to labels
    end if
  end for
end for
Convert data and labels to numpy arrays
train_data, test_data, train_labels, test_labels ←
train_test_split(data, labels, test_size = 0.2, random_state = 42)
train_data_flat ← reshape train_data to 2D
test_data_flat ← reshape test_data to 2D
Initialize Decision Tree model dt_model
Train dt_model on train_data_flat and train_labels
predictions ← dt_model.predict(test_data_flat)
accuracy ← accuracy_score(test_labels, predictions)
print Accuracy
print Classification Report
Compute precision, recall, f1_score per class
Plot precision, recall, f1_score per class and overall accuracy
```

Algorithm 1 Image Classification with SVM and MSVM

```
Input: dataset_path, categories
Output: Final accuracy and classification report
Initialize empty lists data and labels
for category in categories do
  folder_path ← concatenate dataset_path and category
  for img_name in list of image names in folder_path do
    img_path ← concatenate folder_path and img_name
    img ← read image from img_path
    img ← convert image to RGB format
    img ← resize image to (100, 100)
    glsm_features ← calculate GLSM features for img
    append glsm_features to data
    append category index to labels
  end for
end for
Convert data and labels to numpy arrays
Split the dataset into training and testing sets:
  X_train, X_test, y_train, y_test
Train an SVM model: svm ← SVC(kernel='linear'); svm.fit(X_train, y_train)
Make predictions using the SVM model: predictions_svm ←
  svm.predict(X_test)
Train a NuSVC model using SVM predictions: msvm ←
  NuSVC(kernel='linear'); msvm.fit(X_train, y_train)
Make predictions using the MSVM model: predictions_msvm ←
  msvm.predict(X_test)
Calculate final accuracy: final_accuracy ←
  accuracy_score(y_test, predictions_msvm)
Print Final Accuracy : final_accuracy
Print classification report: classification_report(y_test, predictions_msvm)
Plot precision, recall, and F1-score for each class:
for i in range(len(categories)) do
  Plot precision, recall, and F1-score for class i
end for
```

4. RESULTS AND EXPERIMENTS

The grape diseases dataset sourced from Kaggle is a well-structured collection designed for detecting and classifying grape plant conditions using machine learning models. It comprises 800 high-resolution images, evenly divided into 400 diseased and 400 healthy samples, providing a balanced dataset for effective model training and evaluation. The dataset includes diverse images captured under varying lighting conditions, angles, and backgrounds, ensuring robustness in real-world applications. These images facilitate detailed texture and feature analysis, crucial for accurate disease identification. Developed in Python, the dataset is used with image processing and machine learning libraries such as OpenCV, TensorFlow, and Scikit-learn to extract relevant features and train models for automated disease classification. The dataset's composition allows for deep learning models like Convolutional Neural Networks (CNNs) and machine learning techniques like Support Vector Machines (SVMs) to be effectively trained and validated. This contributes to precision agriculture by enabling early disease detection, reducing reliance on manual inspections, and enhancing vineyard management through data-driven insights.

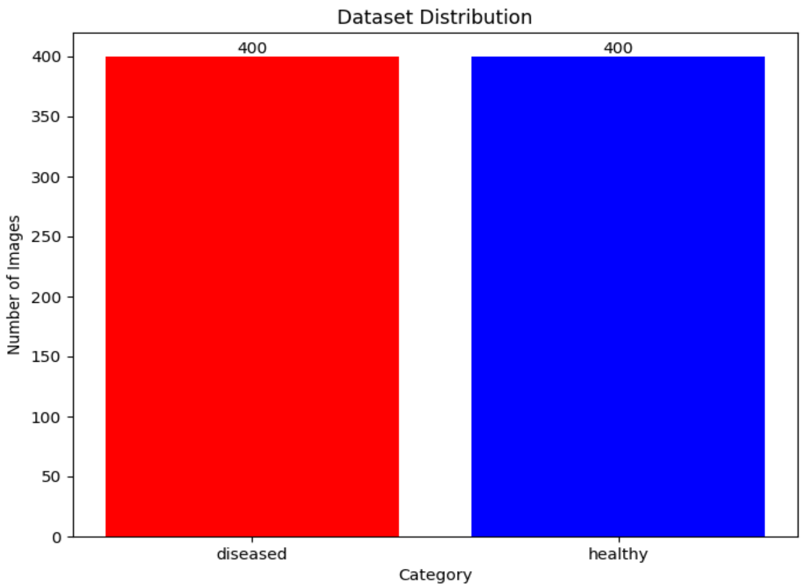

Fig 4.1 Dataset Distribution

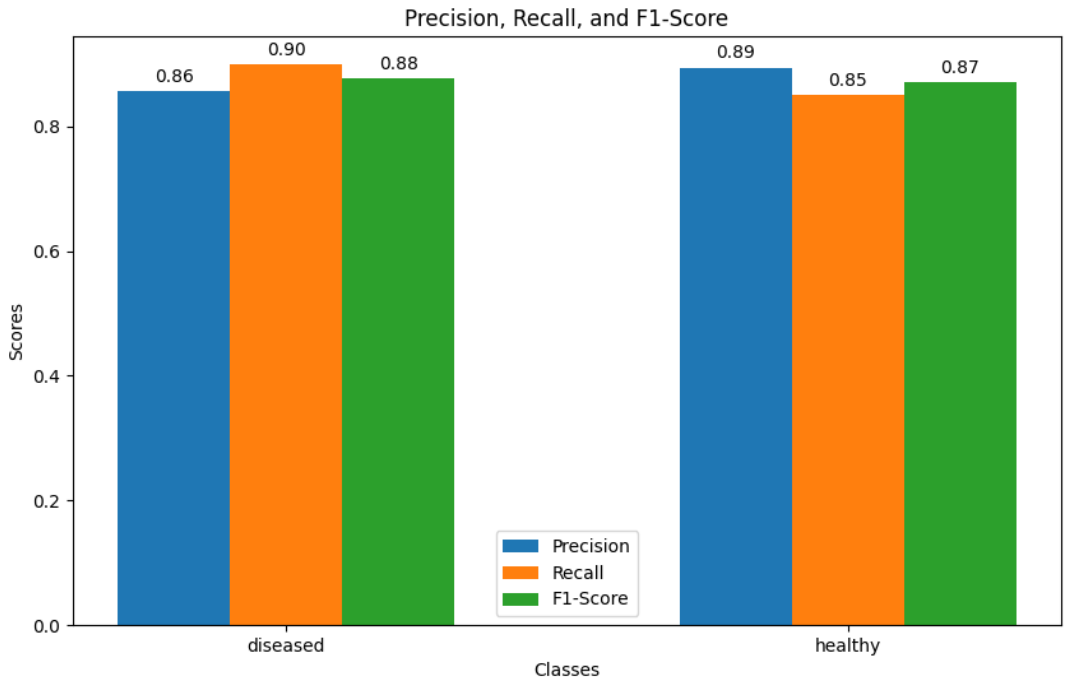

Fig 4.2 Performance Metric Hybrid SVM-MSVM implementation

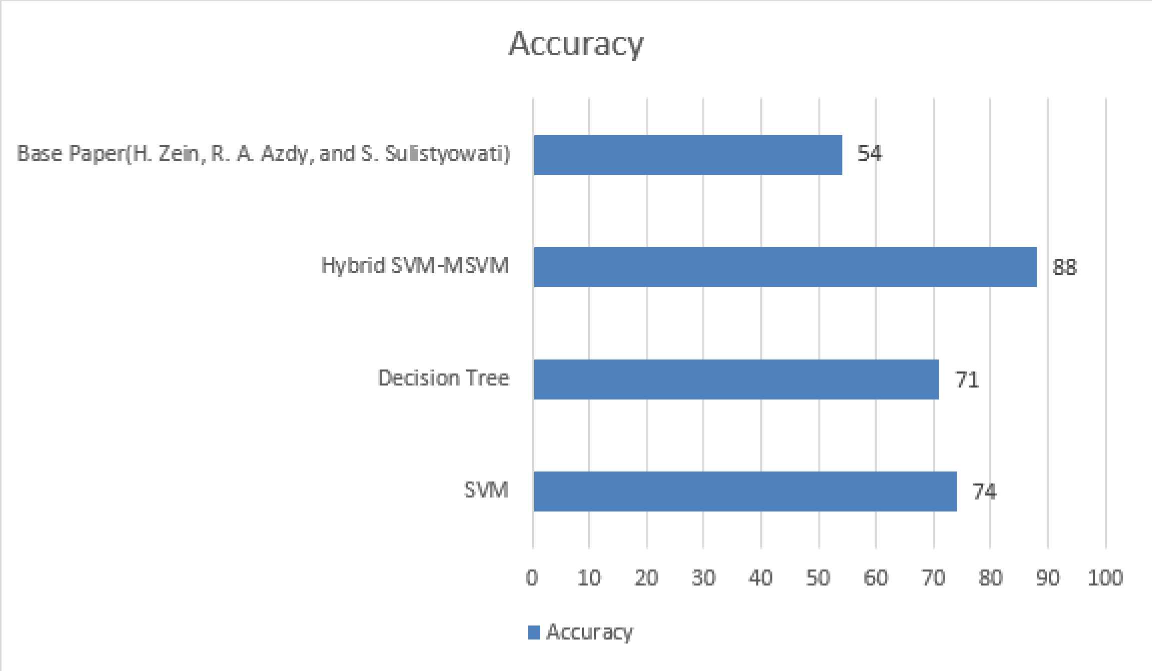

Fig 4.3 Accuracy Results Comparison

5. CONCLUSION

The integration of machine learning and image processing techniques in precision agriculture offers a promising solution for the early detection and classification of grape diseases. This study presented an automated disease detection framework using Gray-Level Co-Occurrence Matrix (GLCM) for texture feature extraction and Multi-Class Support Vector Machine (SVM) for classification. By analysing texture-based features such as contrast, correlation, energy, and homogeneity, the proposed model effectively differentiates between healthy and diseased grape leaves, addressing key challenges in viticulture disease management. The use of a well-curated dataset with diverse image conditions enhances the model's robustness and generalization capabilities, ensuring reliable performance in real-world vineyard settings.

The findings of this study highlight the potential of machine learning in reducing dependency on manual disease inspection, optimizing pesticide usage, and improving overall vineyard productivity. By integrating automated disease detection into precision agriculture, farmers can make informed decisions, prevent large-scale disease outbreaks, and adopt sustainable farming practices. Future work can focus on enhancing classification accuracy by incorporating deep learning approaches such as Convolutional Neural Networks (CNNs) and expanding the dataset to include additional grape diseases. Furthermore, real-time deployment of the proposed system through mobile applications or embedded IoT-based solutions can further revolutionize grape disease monitoring and vineyard management.

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