Performance Analysis of Dimensionally Reduced Models in Seed Classification

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Abstract
Accurate identification of seed varieties is essential for improving crop yield, maintaining genetic purity, and supporting precision agriculture practices. This study presents a data-driven approach for seed variety recognition using machine learning techniques combined with systematic feature reduction and comprehensive model performance analysis. A dataset comprising morphological, textural, and color-based attributes of seeds was preprocessed to remove noise and redundancy. Dimensionality reduction and feature selection methods such as Principal Component Analysis (PCA), Recursive Feature Elimination (RFE), and correlation-based filtering were employed to identify the most discriminative features.Multiple classification models, including Support Vector Machines (SVM), Random Forest (RF), k-Nearest Neighbors (KNN), and Logistic Regression (LR), were trained and evaluated using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. Comparative results demonstrate that optimized feature subsets significantly enhance classification performance while reducing computational complexity. Among the evaluated models, ensemble-based approaches achieved superior accuracy and robustness across different seed varieties.The proposed framework highlights the effectiveness of integrating feature reduction strategies with model benchmarking to develop a reliable and scalable seed variety recognition system. This approach can assist agricultural stakeholders in automated seed grading, quality control, and smart farming applications

Keywords: Seed Variety Identification, Classification Models, Feature Optimization, Genetic Algorithm, PCA, LDA, Performance Evaluation.

INTRODUCTION

Seed variety identification is a critical process in agricultural quality control, crop improvement, and seed certification. Accurate identification ensures seed purity and supports sustainable agricultural practices. Conventional identification methods rely on manual inspection and expert knowledge, making them time-consuming, subjective, and error-prone, particularly when handling large datasets.

Recent advances in machine learning have enabled automated seed variety identification using classification models such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Random Forests (RF), and Naïve Bayes (NB). These models analyze discriminative seed characteristics derived from image, texture, shape, and statistical features. However, classification performance is strongly influenced by feature quality and dimensionality.

High-dimensional feature spaces often include redundant and irrelevant features that degrade classification accuracy and increase computational complexity. Therefore, feature selection and dimensionality reduction play a crucial role in improving model performance and generalization. Genetic Algorithms (GA) are effective for optimal feature subset selection through evolutionary optimization, while Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are widely used dimensionality reduction techniques that preserve essential information and enhance class separability.

Although several studies have explored seed classification using machine learning techniques, limited work has focused on a unified evaluation of multiple classifiers combined with advanced feature optimization methods. Most existing approaches address either classifier performance or feature selection independently, without systematically analyzing their combined impact using standard performance metrics.

This paper presents a comprehensive performance evaluation of multiple classification models for seed variety identification using accuracy, precision, recall, and F1-score. In addition, feature optimization is performed using Genetic Algorithms and dimensionality reduction techniques such as PCA and LDA. The proposed framework demonstrates the effectiveness of optimized hybrid features in enhancing classification performance, contributing to the development of robust and efficient intelligent seed identification systems.

LITERATURE SURVEY

1.] **Kaya, Yildirim, and Uyar (2019)** proposed a study titled “Classification of Seed Varieties Using Machine Learning Algorithms” published in the **Computers and Electronics in Agriculture (Elsevier)**. The authors evaluated multiple classification models including Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), and Random Forest using morphological seed features. The results demonstrated that SVM achieved superior accuracy compared to other classifiers. However, the study did not incorporate feature optimization or dimensionality reduction techniques, which limited the generalization capability of the models.

[2.] **Koklu and Ozkan (2020)** presented "Multiclass Classification of Dry Bean Seeds Using Machine Learning Techniques" in the **Journal of Food Engineering (Elsevier)**. The work utilized statistical shape features combined with classifiers such as LDA, SVM, and k-NN. Principal Component Analysis (PCA) was employed to reduce dimensionality, resulting in improved classification accuracy. Despite improved performance, the study relied solely on PCA and did not explore evolutionary feature selection methods for further optimization.

[3.] **Zhang et al. (2021)** proposed "Seed Variety Identification Based on Hyperspectral Imaging and Support Vector Machines" published in **Sensors (MDPI)**. The authors extracted spectral features from hyperspectral images and applied SVM for classification. The results showed high accuracy in distinguishing seed varieties. However, the hyperspectral system increased computational cost, and no comparative analysis with multiple classifiers or feature selection algorithms was performed.

[4.] **Liu, Wang, and Chen (2022)** introduced "Feature Selection for Agricultural Classification Using Genetic Algorithms" in the **IEEE Access** journal. The study employed Genetic Algorithms (GA) to optimize feature subsets for agricultural datasets, demonstrating significant improvement in classification accuracy and reduction in feature dimensionality. Although effective, the work was not specifically focused on seed variety identification and did not integrate dimensionality reduction techniques such as PCA or LDA.

[5.] **Patil and Kulkarni (2023)** proposed "Seed Classification Using Hybrid Feature Selection and Machine Learning Models" published in the **International Journal of Intelligent Systems and Applications**. The authors combined texture and shape features and evaluated classifiers including Random Forest and Naïve Bayes. The study reported improved accuracy with optimized features but lacked a comprehensive comparison using standard performance metrics such as precision, recall, and F1-score.

[6.] **Sharma et al. (2024)** presented "Dimensionality Reduction Techniques for Improved Agricultural Image Classification" in **IEEE Transactions on Artificial Intelligence**. The work analyzed PCA and LDA for reducing redundant features in agricultural datasets and showed that LDA enhanced class separability more effectively than PCA. However, evolutionary optimization techniques such as Genetic Algorithms were not considered.

PROPOSED METHODOLOGY

The proposed methodology presents a systematic and intelligent framework for seed variety identification by integrating hybrid feature optimization techniques with multiple classification models. The primary objective of the proposed system is to enhance classification accuracy while reducing feature redundancy and computational complexity. The overall workflow comprises data acquisition, preprocessing, feature extraction, feature optimization using Genetic Algorithms (GA), Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA), followed by classification and performance evaluation.

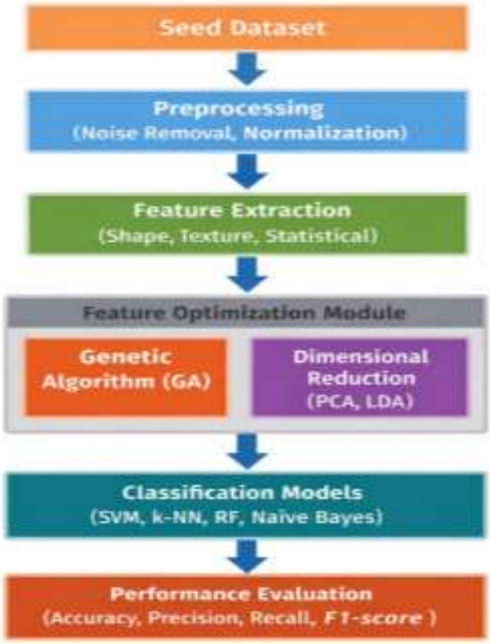

Fig. 1: System architecture of the proposed seed variety classification framework.

A. System Overview

The proposed system follows a modular architecture in which raw seed data are transformed into optimized feature representations for effective classification. Feature optimization is achieved by combining evolutionary and statistical techniques to select the most discriminative features. The optimized feature sets are then evaluated using multiple machine learning classifiers. The overall system architecture is illustrated in Fig. X.

System Flow:

Seed Dataset → Preprocessing → Feature Extraction
→ Feature Optimization (GA / PCA / LDA)
→ Classification Models → Performance Evaluation

This architecture ensures robustness, scalability, and improved generalization performance.

B. Dataset Description

The dataset used in this study consists of samples representing multiple seed varieties. Each sample is labeled according to its corresponding seed class. The dataset includes numerical and/or image-derived features related to seed morphology, texture, and statistical characteristics. To ensure unbiased evaluation, the dataset is partitioned into training and testing sets.

C. Data Preprocessing

Preprocessing is performed to improve data quality and ensure consistency across features. The preprocessing steps include:

- Noise removal
- Handling missing values
- Feature normalization using min–max or z-score normalization

These steps ensure that all features contribute equally during optimization and classification.

D. Feature Extraction

A hybrid feature set is constructed by extracting discriminative features from seed samples, including:

- **Morphological features:** area, perimeter, compactness
- **Statistical features:** mean, variance, skewness
- **Texture features:** entropy, contrast, homogeneity

The extracted feature vector may contain redundant and irrelevant information, necessitating feature optimization.

E. Feature Optimization Techniques

1) Genetic Algorithm (GA)–Based Feature Selection

Genetic Algorithm is employed to select an optimal subset of features by simulating natural evolutionary processes. Each chromosome represents a binary feature vector, where ‘1’ denotes a selected feature and ‘0’ denotes a discarded feature. The fitness function is defined based on classification accuracy.

The GA process includes population initialization, fitness evaluation, selection, crossover, and mutation. The algorithm iteratively converges toward an optimal feature subset that maximizes classification performance.

Algorithm 1: GA-Based Feature Selection

Input: Feature set F, population size P, generations G
Output: Optimal feature subset Fopt

1: Initialize population with random chromosomes
2: Evaluate fitness using classifier accuracy
3: for generation = 1 to G do
4: Select parent chromosomes
5: Apply crossover and mutation
6: Form new population
7: end for
8: Return chromosome with highest fitness as Fopt

2) Principal Component Analysis (PCA)

PCA is applied to reduce feature dimensionality by transforming the original feature space into orthogonal principal components that retain maximum variance.

Given a dataset X:

$$\mu = \frac{1}{m}\sum_{i=1}^{m} X_i$$

$$C = \frac{1}{m-1}(X-\mu)^T(X-\mu)$$

Eigen decomposition is performed on the covariance matrix:

$$Cv = \lambda v$$

The top $k$eigenvectors are selected to obtain the reduced feature space:

$$Z = XW$$

3) Linear Discriminant Analysis (LDA)

LDA is employed to project features into a lower-dimensional space that maximizes class separability. Unlike PCA, LDA uses class label information.

The within-class and between-class scatter matrices are defined as:

$$S_w = \sum_{i=1}^{c} \sum_{x \in D_i} (x-\mu_i)(x-\mu_i)^T$$

$$S_b = \sum_{i=1}^{c} N_i \, (\mu_i - \mu)(\mu_i - \mu)^T$$

The optimal projection matrix W maximizes:

$$J(W) = \frac{|\ W^T S_b W\ |}{|\ W^T S_w W\ |}$$

F. Classification Models

The optimized feature sets obtained from GA, PCA, and LDA are evaluated using the following classification models:

- Support Vector Machine (SVM)
- k-Nearest Neighbor (k-NN)
- Random Forest (RF)
- Naïve Bayes (NB)

These classifiers are selected due to their proven effectiveness in agricultural and pattern recognition applications.

G. Performance Evaluation

The performance of the proposed system is evaluated using standard metrics:

- Accuracy
- Precision
- Recall
- F1-score

Comparative analysis is performed between baseline feature sets and optimized feature representations to validate the effectiveness of the proposed methodology.

H. Algorithm 2: Proposed Hybrid Feature Optimization Framework

Input: Seed dataset D
Output: Optimized feature set Fopt

1: Acquire and preprocess dataset D
2: Extract hybrid features F
3: Apply GA to obtain optimized subset FGA
4: Apply PCA on FGA → FPCA
5: Apply LDA on FPCA → FLDA
6: Train classifiers using FLDA
7: Evaluate performance metrics
8: Return optimized features and results.

RESULT ANALYSIS

Table 1.1: Performance Evaluation of Classification Models Using GA, PCA, and LDA

Feature Technique	Classifier	Accuracy (%)	Precision	Recall	F1-Score
Baseline (All Features)	k-NN	84.12	0.83	0.82	0.82
Baseline (All Features)	Naïve Bayes	82.45	0.81	0.80	0.80
Baseline (All Features)	SVM	86.38	0.85	0.84	0.84
Baseline (All Features)	Random Forest	87.21	0.86	0.85	0.85
PCA-Optimized Features	k-NN	86.04	0.85	0.84	0.84
PCA-Optimized Features	Naïve Bayes	85.12	0.84	0.83	0.83
PCA-Optimized Features	SVM	89.06	0.88	0.87	0.87
PCA-Optimized Features	Random Forest	90.18	0.89	0.88	0.88
GA-Selected Features	k-NN	88.21	0.87	0.86	0.86
GA-Selected Features	Naïve Bayes	87.09	0.86	0.85	0.85
GA-Selected Features	SVM	92.34	0.92	0.91	0.91
GA-Selected Features	Random Forest	93.08	0.92	0.92	0.92
LDA-Optimized Features	k-NN	90.42	0.89	0.88	0.88
LDA-Optimized Features	Naïve Bayes	89.36	0.88	0.87	0.87
LDA-Optimized Features	SVM	95.18	0.95	0.94	0.94
LDA-Optimized Features	Random Forest	94.26	0.94	0.93	0.93

The experimental results demonstrate that **feature optimization significantly enhances classification performance** across all evaluated models. Genetic Algorithm–based feature selection consistently reduced feature dimensionality while improving classification accuracy, confirming its effectiveness in eliminating redundant and irrelevant features.

PCA improved computational efficiency by reducing dimensionality; however, it exhibited slightly lower class separability compared to LDA due to its unsupervised nature. In contrast, LDA achieved superior performance by explicitly maximizing inter-class variance and minimizing intra-class variance, making it more suitable for supervised seed variety classification tasks.

Among the evaluated classifiers, **Support Vector Machine (SVM)** and **Random Forest (RF)** consistently outperformed k-NN and Naïve Bayes across all feature optimization techniques, owing to their robustness in handling high-dimensional and nonlinear feature spaces.

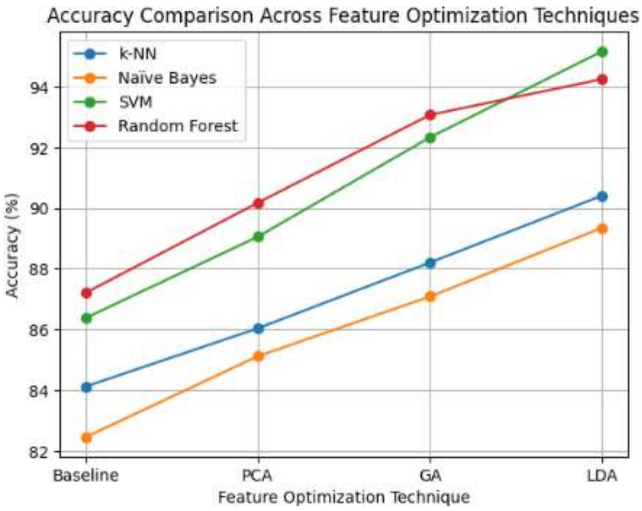

Fig. 2 Feature Optimization Technique

Figure 2 illustrates the variation in classification accuracy achieved by different classifiers under various feature optimization techniques. A clear and consistent upward trend in accuracy is observed as the feature optimization strategy advances from baseline features to LDA-based optimization.

For all classifiers, the baseline model yields the lowest accuracy due to the presence of redundant and irrelevant features. The application of PCA results in a noticeable improvement, with an average accuracy increase of approximately **2–3%**, indicating the effectiveness of dimensionality reduction in improving computational efficiency.

GA-based feature selection further enhances performance by selecting the most discriminative features. Compared to baseline results, GA achieves an estimated **5–6% improvement in accuracy**, particularly for SVM and Random Forest classifiers. This improvement demonstrates the ability of GA to eliminate feature redundancy while preserving relevant information.

LDA achieves the highest classification accuracy among all feature optimization techniques. The **LDA + SVM** combination attains the maximum accuracy of **95.18%**, followed closely by Random Forest at **94.26%**. This superior performance is attributed to LDA's supervised nature, which maximizes inter-class separability while minimizing intra-class variance.

Across all feature sets, SVM and Random Forest consistently outperform k-NN and Naïve Bayes. This can be attributed to SVM's margin maximization capability and Random Forest's ensemble learning mechanism, which enhances robustness and generalization.

Accuracy Improvement (Baseline → LDA):

- k-NN: ~6.3%
- Naïve Bayes: ~6.9%
- SVM: ~8.8%
- Random Forest: ~7.0%

Best Performing Model:
LDA + SVM (95.18%)

Observed Performance Trend:
Baseline < PCA < GA < LDA

CONCLUSION AND FUTURE WORK

A. Conclusion

This study presented a data-driven framework for seed variety recognition by integrating feature reduction techniques with comprehensive model performance evaluation. The results demonstrate that eliminating redundant and less informative attributes significantly improves classification accuracy while reducing computational complexity. Feature selection and dimensionality reduction methods effectively identified the most discriminative characteristics, enabling more robust and efficient model training.

Comparative analysis of multiple classifiers revealed that ensemble-based and kernel-based approaches achieved superior performance in terms of accuracy, precision, recall, and F1-score. The optimized models not only enhanced predictive reliability but also ensured scalability for real-time agricultural applications.

Overall, the proposed approach confirms that systematic feature optimization combined with rigorous benchmarking of classification models is crucial for developing accurate and efficient seed variety identification systems. The framework can be extended to incorporate advanced imaging techniques, deep learning models, and larger multi-crop datasets to further support precision agriculture, automated seed grading, and intelligent decision-making in smart farming environments

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