High-performance forage classification models for smart agriculture: a study on Keras, SVM, and BPNN

Siddique, A[1]; Terrill, TH[1]; Panda, SS[2]; Mahapatra, AK[1]; Xu, Z[3]; Van Wyk, JA[4]

[1] Department of Agricultural Sciences, Fort Valley State University, 1005 State University Drive, Fort Valley, GA 31030, USA; Email: terrillt@fvsu.edu , Aftab.siddique@fvsu.edu , mahapatraa@fvsu.edu; [2]Institute for Environmental Spatial Analysis, University of North Georgia, 3820 Mundy Mill Road, Oakwood, GA 30566, USA; Email: Sudhanshu.Panda@ung.edu; [3]ARS-USDA Plant Science Research Unit, 1991 Upper Buford Circle, Saint Paul, MN 55108, USA; Email: Zhanyou.Xu@usda.gov; [4] Department of Veterinary Tropical Diseases, Faculty of Veterinary Science, University of Pretoria, Private Bag x04, Onderstepoort 0110, South Africa; Email: jan.vanwyk@up.ac.za

*Corresponding Author: Tel: +1-478-287-9001, Email: Aftab.Siddique@fvsu.edu

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Abstract

A robust and accurate image classification model is essential for the development of a smartphone application to help farmers identify forages from weeds. This study focused on developing and comparing three models: Keras-based deep learning, Support Vector Machine (SVM), and Back Propagation Neural Network (BPNN). A total of 1500 images of alfalfa (*Medicago sativa*), sericea lespedeza (*Lespedeza cuneata*), and weeds were used. The Keras model was tested with varying image sizes, batch sizes, and epochs. The highest performance was achieved with an image size of 128, a batch size of 8, and 100 epochs, yielding accuracy, precision, recall, and F1 scores of 99.01%, but with the highest training time of 44.25 seconds. Alternatively, using a smaller image size of 32 and a batch size of 32 with 50 epochs resulted in a lower accuracy of 98.38%, but significantly reduced training time to 9.61 seconds. The SVM model, with a Radial Basis Function (RBF) kernel, had excellent performance metrics, achieving an accuracy, precision, recall, and F1 score of 99.02%, with an exceptionally low training time of 0.059 seconds and a testing time of 0.01 seconds. This indicates the SVM's efficiency and suitability for rapid classification tasks. The BPNN model, tested with an image size of 128 and a neuron structure of over 200 iterations, achieved an accuracy of 98.36%, with a training time of 2.17 seconds and a minimal testing time of 0.0017 seconds, also showing efficient computational performance. The SVM model is recommended for the smartphone application due to its high accuracy, precision, recall, and F1 score, with its minimal computational requirements, making

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it both robust and efficient. This model's attributes align well with the practical needs of farmers for quick and reliable forage identification under field conditions.

Introduction

An effective and precise image classification model is essential for assisting farmers in differentiating forages from field weeds (Islam et al., 2021). In agricultural systems, precise identification of forages is crucial for optimizing livestock feed quality, enhancing farm output, and reducing losses due to poor resource mismanagement (Monteiro et al., 2021). Conventional identification methods are frequently laborious, subjective, and reliant on specialist knowledge, underscoring the necessity for automated solutions capable of operating effectively in practical environments, such as agricultural fields and pastures (Boruah et al., 2024).

Smartphone applications with sophisticated picture classification features can provide an effective solution for farmers by facilitating the swift and accurate identification of forages and weeds (Siddique et al., 2024). The effectiveness of these applications depends on the creation of classification models that achieve a compromise between high accuracy and computational efficiency, especially considering the processing limitations of mobile devices (Zhang et al., 2019). Recent breakthroughs in machine learning, encompassing deep learning, and traditional techniques, like Support Vector Machines (SVM) and neural networks, offer intriguing opportunities for developing such tools (Zhang et al., 2019; Siddique et al., 2024).

This research highlights the urgent necessity for novel and accessible solutions for forage identification through the examination of advanced machine learning techniques. It seeks to address shortcomings in existing agricultural methods by offering a solid technology framework for precision farming instruments customized to the practical needs of farmers through utilization of machine learning approaches to determine the ideal model configuration achieving both high performance and computational efficiency. The study aim was to evaluate these models on their possible incorporation into a smartphone application for agricultural purposes, focusing on their capacity to process field data reliably and efficiently.

Methods

This study utilized a systematic approach to develop and evaluate image classification models for differentiating alfalfa and sericea lespedeza forage plants among field weeds. The dataset comprised images organized into three distinct classes. Images were preprocessed by resizing them to uniform dimensions, normalizing pixel values to a range of 0-1, and calculating fractal dimensions for enhanced feature extraction. Additional preprocessing included data augmentation techniques, such as rotation, translation, and zooming, implemented using the TensorFlow ImageDataGenerator.

Three primary modeling approaches were investigated: traditional machine learning models, a custom Keras-based deep learning model, and pre-trained deep learning architectures. Traditional models, including Support Vector Machines (SVM) and Back Propagation Neural Networks (BPNN), were trained on features extracted from the preprocessed images. Dimensionality reduction for these models was performed using Principal Component Analysis (PCA) to reduce computational complexity. The SVM models were tuned for different kernels (linear, RBF, and polynomial) and penalty parameters (C), while BPNN models were optimized for hidden layer configurations and maximum iterations. A custom Keras-based deep learning model was implemented with multiple dense layers, batch normalization, and dropout for regularization. The model was trained using the Adam optimizer and sparse categorical cross-entropy loss function. Hyperparameter tuning involved experimenting with batch sizes (8, 16), epochs (25, 50), and input image sizes (75x75, 512x512). Early stopping and learning rate reduction callbacks were employed to avoid overfitting and enhance convergence. The image data set was split into a 70:20:10 ratio as training, testing, and validation sets, respectively, for each model tested.

Performance metrics, including accuracy, precision, recall, F1-score, training time, and testing time, were recorded for all models. Hyperparameter tuning was conducted using grid search and cross-validation for SVM and other traditional models. An ensemble model combining SVM and BPNN was developed to leverage the strengths of individual classifiers. Comparative analyses were conducted to identify the best-performing configurations, and results were visualized through confusion matrices and performance plots.

Results

The results highlight the performance evaluation of three classification models—Keras-based deep learning, SVM, and BPNN—for forage identification among field plant weeds. A total of 1500 images were used to develop and test these models, with detailed performance metrics and computational requirements assessed.

The Keras model demonstrated high flexibility in parameter tuning, with image size, batch size, and epochs significantly impacting performance. The optimal configuration, using an image size of 128, a batch size of 8, and 100 epochs, yielded an accuracy of 99.01%, precision of 99.01%, recall of 99.01%, and an F1 score of 99.01%. However, this configuration incurred the highest computational cost, with a training time of 44.25 seconds. In contrast, a smaller image size of 32, batch size of 32, and 50 epochs achieved slightly reduced accuracy (98.38%), but considerably decreased the training time to 9.61 seconds. These results underline the trade-off between model accuracy and computational efficiency.

The SVM model, employing a Radial Basis Function (RBF) kernel, emerged as the most computationally efficient among the three models. It achieved accuracy, precision, recall, and F1 scores of 99.02%, with a remarkably low training time of 0.059 seconds and a testing time of just 0.01 seconds. These metrics demonstrate the SVM model's capability for rapid and accurate classification, making it highly suitable for applications requiring minimal computational resources.

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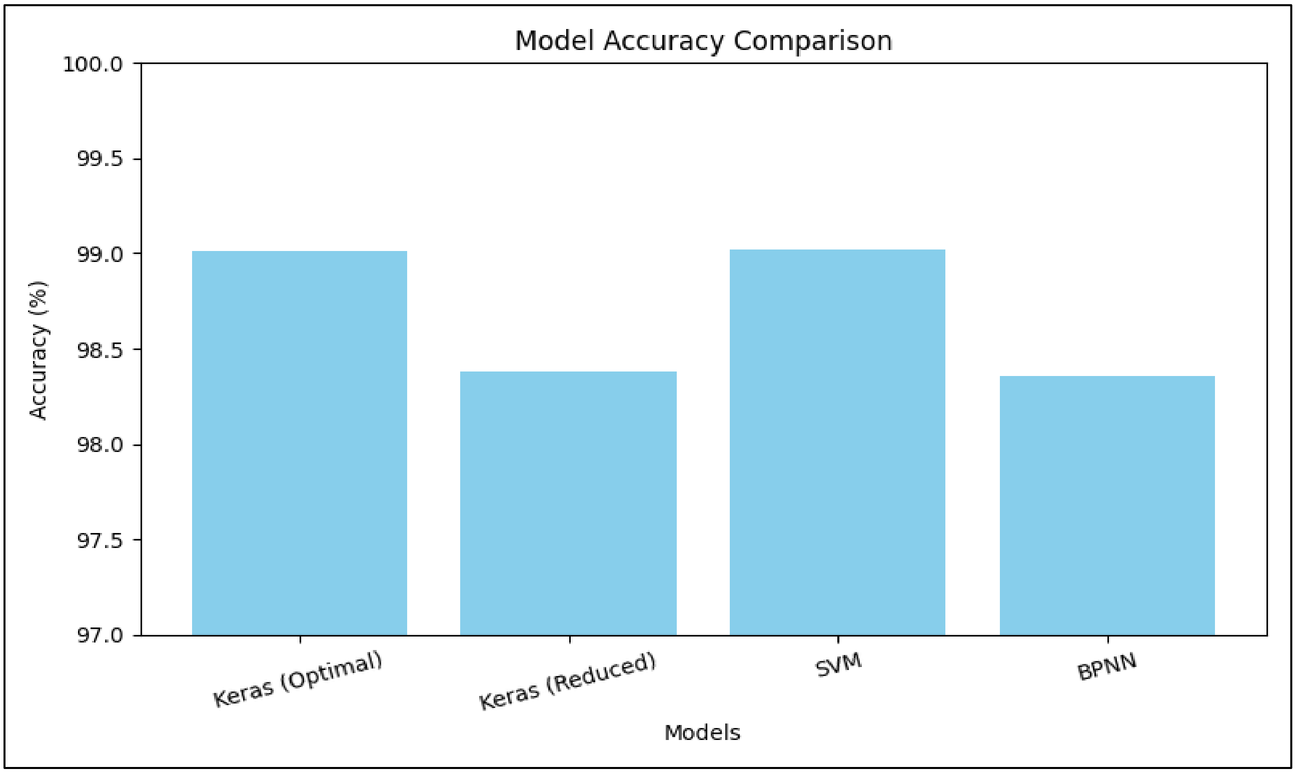

Figure 1. Graphical representation of different models for the accuracy in identification of different forage species.

The BPNN model, tested with an image size of 128 and a neuron structure across 200 iterations, achieved an accuracy of 98.36%. While its performance was slightly lower than the Keras and SVM models, it demonstrated excellent computational efficiency, with a training time of 2.17 seconds and a testing time of only 0.0017 seconds. This makes it a viable option when computational constraints are a priority.

Discussion

This study demonstrates the use of image classification in agriculture by building and assessing three machine learning models specifically designed for forage identification among field weeds. The results underscore the advantages and compromises of each model, offering an in-depth examination to inform their practical use.

The Keras-based deep learning model exhibited an accuracy of 99.01% and resilience under optimum conditions. Nonetheless, its substantial processing requirements, evidenced by a training duration of 44.25 seconds, may restrict its applicability in resource-limited settings, such as smartphones. Modifications to image and batch sizes demonstrated the model's flexibility, resulting in a small decrease in accuracy to 98.38% alongside a considerably reduced training duration of 9.61 seconds. This scalability emphasizes the adaptability of deep learning, while also revealing its reliance on accessible computer resources.

The SVM model, utilizing a RBF kernel, proved to be the most effective and feasible choice, attaining the highest accuracy (99.02%) and precision metrics, alongside extremely low computing demands. The training duration of 0.059 seconds and testing duration of 0.01 seconds render it very appropriate for real-time applications. These results corroborate previous studies highlighting the SVM's resilience and

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computational efficacy in managing smaller datasets and non-linear classification challenges (Khawaja et al., 2024; Siddique et al., 2024). The efficiency of the SVM model renders it an exemplary choice for the proposed smartphone application, providing farmers with a swift and dependable diagnostic instrument.

The Back Propagation Neural Network (BPNN) demonstrated exceptional performance, with an accuracy of 98.36% with low training and testing durations of 2.17 seconds and 0.0017 seconds, respectively. Its computational economy renders it suitable for situations necessitating swift processing; nonetheless, its somewhat diminished accuracy indicates it is suboptimal for high-precision jobs in comparison to SVM and Keras models. These findings validate earlier research that recognized BPNN as an efficient lightweight alternative for limited contexts (Siddique et al., 2024).

This study's main contribution is the construction and comparative analysis of machine learning models for a smartphone application designed for forage identification. The SVM model excels as the most pragmatic option because of its excellent accuracy and computational economy. This approach corresponds with the practical limitations faced by farmers, who necessitate swift, dependable, and resource-efficient solutions for agricultural production challenges. This research's ramifications also transcend forage detection, demonstrating the potential of incorporating machine learning into agricultural tools to improve production and decision-making.

Subsequent research should investigate the scalability of these models for larger and more heterogeneous datasets, along with their applicability to multi-class classification problems. Moreover, incorporating the SVM model into user-friendly smartphone interfaces could augment its practical utility, facilitating the adoption of smart farming technology. This study establishes the foundation for resource-efficient, AI-driven agricultural solutions, connecting advanced technology with practical field application.

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