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Performance Evaluation Of Optimized Wheat Classification Models With Hyperparameter Tuning

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Abstract

In recent years, wheat classification has seen vast improvements with the integration of machine learning. The classification's efficacy, however, heavily depends on the careful tuning of model parameters. This paper reviews advancements in wheat classification models, emphasizing hyperparameter optimization techniques. Various tuning methods such as Grid Search, Random Search, Bayesian Optimization, and others are explored in the context of wheat classification. Ultimately optimized models promise high accuracy and efficiency, challenges such as over-tuning, scalability, and computational costs are discussed in later in this article. The review also revealed the key role of hyperparameter tuning in advancing wheat classification, opening the novel way for better agricultural outcomes.

Keywords: Wheat classification, machine learning, hyperparameter optimization, Grid Search, Random Search, Bayesian Optimization,

1. Introduction

In recent years, wheat, a crop critical for global food security, has witnessed a surge in demand. This necessitates the effective classification of its varieties, quality, and disease status. (Yadav et al. 2020) Traditional wheat classification methods, such as manual inspection, where experts visually examine the wheat, and basic statistical models, which use simple mathematical formulas to classify the wheat], have served as the cornerstone techniques for decades. However, with the advent of advanced computational technologies, machine learning has emerged as a powerful tool in modern agriculture. (Hassan et al. 2018)

The integration of machine learning in wheat classification has its challenges. However, it also introduces a wide array of algorithms, each with its unique set of parameters that can drastically enhance model performance. This presents exciting opportunities for advancements in our field. Consequently, a vital aspect of this process is hyperparameter tuning, which involves adjusting these parameters to ensure classification models' accuracy and efficiency. (Patrício et al. 2018)

While Figure 1 (Hyperparameter tuning and cross-validation) is not explicitly discussed here, it likely showcases the interplay between these techniques. The importance of hyperparameter tuning extends beyond just enhancing model performance. (Sarker et al. 2021) It's about striking a balance between accuracy and computational efficiency, mitigating the risk of over fitting, and ensuring that models generalize well to data not previously encountered. Given the critical role of wheat in global food supply chains, achieving optimal classification is not just an academic exercise but a necessity for sustainable agriculture. (De Winne et al. 2016) Your work directly contributes to this goal, and we are confident in the impact it will have.

This article aims to provide a comprehensive overview of the advancements in wheat classification models, focusing on the techniques and methodologies of hyperparameter tuning.

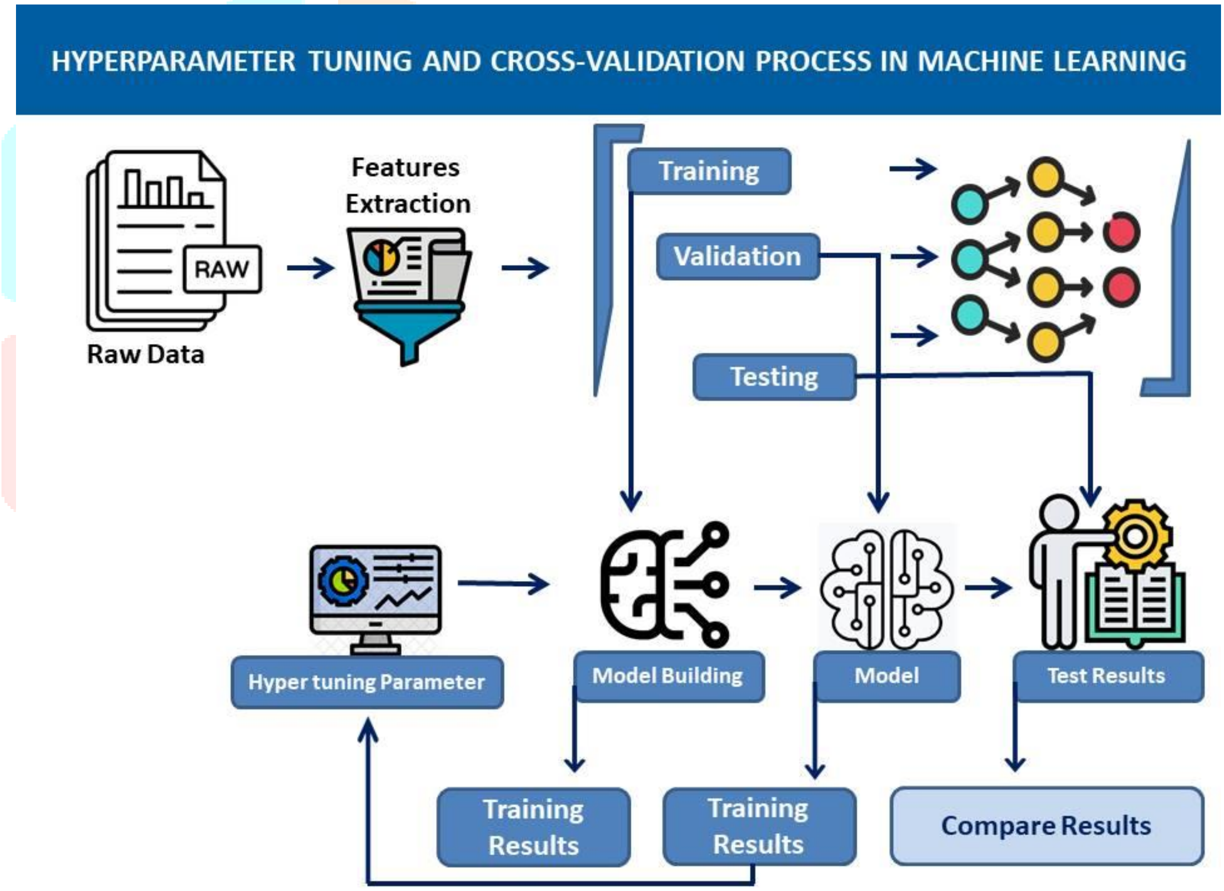

Figure 1: General Hyper parameter tuning and cross-validation flow that are frequently used by various studies that are included in this review

2. Traditional Wheat Classification Methods

2.1. Manual Inspection

Before the advent of sophisticated computational methods and advanced technologies, manual inspection constituted the primary approach for wheat classification. This method relies heavily on the physical examination of wheat grains, leaves, and stems to determine their type, quality, and health status. (Agarwal et al. 2023)

Manual inspection success hinges mainly on the expertise and experience of the examiner, often requiring specialized training as a cornerstone of accurate assessment. (Caballero et al. 2023) Wheat grains undergo a visual assessment of their size, colour, shape, and any surface defects or blemishes. Determining the type of wheat, such as hard red, soft red, durum, or white wheat, is based on grain morphology (shape and structure) and texture. For disease detection, manual inspection often involves studying the phytopathological (plant disease) symptoms on wheat plants, such as discoloration, spots, or necrosis, to diagnose a range of prevalent wheat diseases like rust, smut, or blight. (Zhang et al. 2022)

While manual inspection has demonstrably served as a reliable method for centuries, it is inherently time-consuming and intrinsically susceptible to human error. For instance, subtle differences in wheat grain types or the early stages of disease development may go unnoticed during a manual examination. Moreover, the inspection's outcome can vary among experts, leading to inconsistent classification results.

Despite its limitations, manual inspection provides a valuable ground truth, especially when training machine learning models or validating the results of more advanced classification techniques.

2.2. Basic Statistical Models

Limitations of manual wheat classification methods, such as subjectivity and inconsistency, spurred researchers to explore data-driven approaches. Statistical models emerged as a powerful tool for addressing these challenges. These models rely on quantifiable data collected from the physical characteristics of wheat samples. The models achieve objective and scalable classification based on pre-defined criteria by employing robust statistical techniques. This shift towards data-driven analysis marked a significant advancement in wheat classification research. (Khatri et al. 2022)

2.2.1. Linear Discriminant Analysis (LDA)

One widely adopted technique is Linear Discriminant Analysis. It seeks to identify linear combinations of features that optimally separate two or more classes (Fisher, 1936). LDA has been employed in wheat classification to differentiate wheat varieties based on grain morphometric traits (size and shape), demonstrating a substantial increase in classification accuracy compared to manual methods. (Li et al. 2005)

2.2.2. Cluster Analysis

Cluster Analysis, has been used to group similar wheat varieties based on phenotypic (observable characteristics) and genotypic traits (genetic makeup). Hierarchical clustering methods, in particular, have effectively constructed a "family tree" of wheat germplasm resources, aiding in understanding their evolutionary relationships and grouping them based on genetic similarity. (Everitt et al. 1974)

2.2.3. Principal Component Analysis (PCA)

Principal Component Analysis (PCA), a dimensionality reduction technique, has been instrumental in visualizing multi-dimensional wheat data in two or three dimensions. This visualization facilitates the identification of patterns and clusters among different wheat varieties or categories.

While basic statistical models represent a significant advancement over manual inspection, they have limitations. Most notably, they assume linear relationships among features, which may only sometimes hold for complex agricultural data, such as wheat quality traits influenced by intricate biochemical pathways. Nevertheless, these models laid the foundation for the more sophisticated machine learning algorithms employed in recent years. (Mickiewicz et al. 1993)

2.3. Initial Machine Learning Models

The rise of digital data analysis techniques in the late 20th century coincided with a significant shift towards the application of machine learning algorithms. This advancement had a profound impact on various scientific fields, including agriculture and, specifically, wheat classification. Decision trees emerged as one of the earliest and most intuitive machine-learning tools. Their inherent interpretability, resembling a flowchart of decision-making steps, facilitated comprehension and validation of the classification process by agricultural researchers. Notably, Kahtri et al. (1986) also demonstrated the effectiveness of the Classification and Regression Trees (CART) algorithm in classifying wheat based on multiple physical characteristics such as grain size, shape, and texture. Inspired by the structure of the human brain, Neural Networks were another early innovation in machine learning. Lu et al. (2020) elaborated on the back propagation algorithm for training multi-layer perceptrons. This neural network model was later applied to wheat disease detection. It showcased its ability to identify intricate patterns in large datasets, potentially including subtle spectral signatures indicative of specific pathologies like fungal infections or nutrient deficiencies.

2.4. Support Vector Machines (SVMs)

Support Vector Machines (SVMs) were also introduced as a potent model for wheat classification. Vapnik (1995) explained the mathematical foundation of SVMs, which focuses on maximizing the margin between classes. SVMs were subsequently employed to classify wheat grains accurately, especially in cases with a clear margin between classes.

The initial machine learning models offered several advantages, including the ability to handle large datasets and uncover non-linear patterns. However, they also presented challenges like over fitting and required careful pre-processing and feature engineering to achieve optimal performance (Gavrilov et al., 2018).

3. Optimizing Machine Learning Models for Wheat Classification

The widespread adoption of machine learning for wheat classification has necessitated a focus on model optimization. While inherently capable of handling large datasets and complex patterns, machine learning models can deviate from their intended accuracy and efficiency if not properly optimized.

3.1. Reducing Overfitting

Over fitting remains a prevalent challenge in machine learning, particularly relevant to wheat classification. Over fitting occurs when a model prioritizes the training data excessively, sacrificing its ability to generalize effectively to unseen data. The model becomes overly attuned to specific details and noise within the training data, leading to poor performance in real-world scenarios (Gavrilov et al., 2018). Several other factors can also contribute to over fitting in wheat classification models:

4. Complex Models:

Deep learning architectures or models with extensive parameters can readily capture noise or irrelevant patterns within the data (Bhardwaj et al 2023).But there are some limitations when dealing with constrained datasets, models may inadvertently learn specific characteristics of the samples, like subtle variations in grain morphology (e.g., size, shape, presence of awns) or spectral signatures indicative of specific biochemical compositions, rather than general features that define wheat categories.

4.1. Redundant Features

Including irrelevant or highly correlated features, such as redundant spectral signatures, in the training process can skew the model's decision boundaries Kahtri et al. (1986).

The consequences of over fitting in wheat classification can be significant. For instance, an over fitted model might misclassify a healthy wheat sample with a slight morphological anomaly as diseased, leading to unnecessary treatments or discarding healthy yield.

Established techniques such as regularization, cross-validation, and pruning have been widely adopted to counteract over fitting Zhang et al. 2022). Regularization introduces penalty terms to the model's loss function, constraining its complexity and preventing overfitting. Cross-validation, particularly k-fold cross-validation, allows for a more robust evaluation of the model's performance on unseen data. In the case of decision trees, pruning helps eliminate unnecessary branches that do not significantly contribute to classification accuracy, promoting a more parsimonious model.

4.2. Enhancing Classification Accuracy

Accuracy remains a pivotal metric in wheat classification, determining the model's ability to classify wheat samples based on their biological properties correctly. However, achieving high accuracy can be challenging due to various factors, such as data imbalance (e.g., overrepresentation of healthy wheat compared to diseased samples), noise within the dataset (e.g., variations in image quality), and the inherent variability of agricultural samples due to factors like genetics and environmental conditions.
There are several compelling reasons to prioritize enhancing accuracy in wheat classification:

4.3. Economic Implications:

Inaccuracy in classification can lead to financial losses, as misclassified wheat can affect its market value or discard healthy yield (Stone & Brooks, 1990).

4.4. Safety and Health Concerns:

Misclassifying diseased wheat as healthy can pose health risks if it enters the food chain (Wilkinson et al., 2000).

4.5. Resource Optimization:

Accurate classification allows for better resource allocation in terms of treatments (e.g., fungicides for fungal diseases, insecticides for pest control), storage (separating healthy from diseased grain), and distribution (ensuring quality grain reaches consumers).

To strengthen accuracy, various methodologies and techniques have been adopted:

5. Ensemble Methods

These methods combine multiple models to achieve better accuracy than a single model. Techniques such as bagging and boosting have significantly improved accuracy (Dietterich, 2000).

5.1. Feature Selection and Engineering

Selecting the most relevant features, such as those related to grain size, shape, texture, spectral signatures, and protein content, or creating new features that can capture essential patterns in the data can significantly enhance model performance (Guyon & Elisseeff, 2003).

5.2. Data Augmentation

Especially in cases of limited data, artificially increasing the dataset size by introducing slight modifications to existing data (e.g., rotating, zooming images of wheat kernels) can help in training more robust models ((Gavrilov et al., 2018).

5.3. Transfer Learning

Leveraging pre-trained models on large datasets of biological images and fine-tuning them for specific tasks, like wheat classification, can lead to significant improvements in accuracy (Tan et al., 2018).

5.4. Computational Efficiency Considerations

The growing adoption of machine learning for wheat classification has heightened the need for efficient models that can be rapidly trained and deployed. Computational efficiency plays a crucial role in terms of speed and cost.

6. Overview of Hyperparameter Tuning

Hyperparameter tuning plays a pivotal role in optimizing machine learning models. Unlike parameters learned from the data during training, hyperparameters are set before the training begins. Their proper configuration can significantly enhance a model's performance. In wheat classification, the importance of tuning hyperparameters is underscored by the potential benefits of maximizing accuracy, improving generalization, and ensuring computational efficiency (Litjens et al . 2019).

6.1. Grid Search

One of the most straightforward and commonly used methods for hyperparameter tuning is Grid Search. It entails exhaustively searching through a manually specified subset of the hyperparameter space.

6.1.1. Procedure: A discrete set of values is predefined for each hyperparameter. Grid Search then trains a model for every combination of these hyperparameter values, evaluating each model using cross-validation (Litjens et al . 2019).

6.1.2. Advantages: Grid Search is comprehensive because it examines all possible combinations of the provided hyperparameter values. This meticulous approach often yields the best results within the specified grid.

6.1.3. Limitations: The primary limitation is its computational cost. As the number of hyper parameters and their potential values increase, the number of combinations grows exponentially, making the search time-consuming. Furthermore, since the values are specified beforehand, Grid Search does not guarantee the finding of the optimal hyper parameters if they lie outside the predefined grid (Bergstra & Bengio, 2012). Use in

Wheat Classification: For instance, when classifying wheat using a support vector machine, hyperparameters like the regularization parameter and kernel type can be optimized using Grid Search to ensure maximum classification accuracy (Vapnik, 1995).

6.2. Random Search

An alternative to the exhaustive nature of Grid Search, Random Search samples hyperparameters from a distribution over the possible parameter values. This method has proven to be surprisingly effective and often more efficient than Grid Search, especially when the number of hyperparameters is large.

6.2.1. Procedure: Rather than checking every single combination of hyperparameters, Random Search randomly selects a set of hyperparameters from a distribution for each iteration. It continues for a fixed number of iterations or until a convergence criterion is met (Bergstra & Bengio, 2012).

6.2.2. Advantages: Random Search can be more efficient than Grid Search because it doesn't necessarily evaluate all possible combinations. Instead, it randomly samples them, which can often lead to good hyperparameters in less time. The method is particularly useful when some hyperparameters are more critical than others since it doesn't waste time on the less influential ones (Bergstra & Bengio, 2012).

6.2.2. Limitations: A potential downside is that Random Search doesn't provide a systematic exploration of the hyperparameter space. Thus, there's a chance that certain promising regions might be overlooked.

6.3. Bayesian Optimization

Bayesian Optimization is an advanced method for hyperparameter tuning that builds a probabilistic model of the objective function to be optimized. It's particularly suited for high-dimensional optimization tasks where the objective function is expensive to evaluate.

6.3.1. Procedure: Bayesian Optimization utilizes a probabilistic model, usually a Gaussian Process (GP), to estimate the function's distribution. At each step, an acquisition function, such as Expected Improvement (EI) or Upper Confidence Bound (UCB), is employed to decide where to sample next, trading off between exploration (sampling where the uncertainty is high) and exploitation (sampling where the estimated function value is low). Iteratively, the method refines its estimates and converges to the optimal set of hyperparameters (Snoek et al., 2012).

6.3.2 Advantages: One of the main strengths of Bayesian Optimization is its efficiency. Because it models the objective function probabilistically, it tends to require fewer function evaluations than methods like Grid Search or Random Search. This characteristic makes it ideal for optimizing machine learning models where training or evaluation is computationally expensive (Shahriari et al., 2016).

6.3.2. Limitations: Bayesian Optimization can be sensitive to the choice of kernel for the GP and the acquisition function. Also, as the number of hyperparameters grows, the method can become computationally intensive, given the need to invert large covariance matrices in GPs (Brochu et al., 2010).

7. Discussion

Identifying wheat varieties using traditional methods takes a lot of time. With modern methods like artificial intelligence and machine learning, we can speed it up a lot. Apart from this, we can also increase the accuracy of its identification. Traditional methods have some limitations. As a result, understanding human error and statistical complexities is very difficult. Statistical models mostly depend on linear relationships. However, they also struggle to grasp the intricacies of agriculture. Effectiveness of an ML algorithm depends on its hyper-tuning features. These parameters are important for training the model. Consequently, these parameters have an impact on the model's final output. The goal of these models is to find the best solution. This search is based on the model's data quality and quantity. Grid search, random search, and Bayesian optimisation are the major techniques used for hyper parameter tuning, which also have their own limitations, advantages, and disadvantages. In machine learning, support vector machines (SVMs) act as a great distinguisher on the hyper plane that perfectly separates data points between two or more different groups. They work particularly well with complex biological or research problems, even when there is not much training data available. Some machine learning methods, like random forests, combine the strengths of multiple decision trees. This makes them less likely to over fit the data, and they are able to handle both descriptive categories (such as type of wheat) and continuous measurements (such as grain size). Another powerful tool for classifying wheat varieties based on grain size, texture, and disease symptoms is Convolutional Neural Networks (CNN), which analyses images. Hyper tuning relies heavily on parameter adjustments to get better results from any machine learning approach; hyper tuning relies heavily on the adjustment of parameters. Being able to classify wheat accurately and efficiently is crucial for world food security. While old-fashioned methods, such as hand-checking and basic statistical models, have been useful in the past, they have limitations. This paper will explore advances in machine learning (ML) algorithms for wheat classification, with a particular focus on how important it is to adjust key settings.

We can use machine learning approaches to analyse wheat properties, just as we do with genetic data in bioinformatics. We can also comprehend intricate patterns that are challenging to clear. Support vector machines correct the reinforce data, random forests combine it, and convolutional neural networks evaluate images. We can improve the model by adjusting hyper parameters to reduce over fitting. Using this method in hyper parameter tuning and transfer learning can help find interesting ways, even though it takes a lot of time.

SVMs is best in finding hyper planes that optimally separate data points particularly effective for high-dimensional data and can handle limited training data set more efficiently. Ensemble learning technique combines multiple decision trees and reduces over fitting and in good in and handling both categorical and continuous dataset. In case of image data for wheat variety classification tasks, CNNs can be a powerful tool. Because of their architecture, extracting features efficiency from images of grain shape, texture, and potential disease symptom. Selection of the most suitable algorithm depends on the specific classification task and and quality and quantity of dataset. However, regardless of the selection of suitable algorithm, their optimal performance is must consider crucial step for hyper parameter tuning. Ensuring efficient and accurate wheat classification is must needed for global food security. This article explains the advancements in machine learning (ML) algorithms for wheat classification, with a particular emphasis on the critical role of hyper parameter tuning.

It is critical to adjust hyper parameters in order to optimize the performance of a machine learning model. Hyper parameters significantly influence the model's behaviour and dictate the learning process. The goal is to find the optimal configuration that maximizes precision, ensuring dependable categorization of wheat varieties. This process can benefit from tuning techniques including random search, grid search, and Bayesian optimization, each of which has its own benefits and drawbacks. The implementation of a method depends on the available computing capacity and the number of hyper parameters. Wheat classification can benefit from hyper parameter tuning, as optimal tuning provides numerous advantages. Calibration achieves enhanced precision by accurately categorizing wheat varieties. Reducing over fitting enhances the performance of models on new data, thereby enhancing the learning process. Additionally, increased efficacy reduces the amount of time and energy required, enabling specialists to examine a greater number of models and configurations. Models that are more interpretable are easier to understand. Researchers can gain insight into the model's functionality. Hyper parameters influence the classification choices, providing valuable biological insights into the model's decision-making process.

8. Conclusion

This article demonstrates that artificial intelligence and machine learning algorithms may effectively enhance the categorization of different types of wheat. However, the hyper parameter tuning method may enhance their effectiveness significantly. This has the capacity to provide several advantages for farmers. This includes ensuring the highest possible quality of crops, promptly identifying illnesses, and making well-informed decisions. Researchers have the capacity to significantly contribute to the development of the world food supply, therefore enhancing its security and sustainability. When researchers employ the right blend of machine learning and hyper parameter adjustments, they can make significant progress.

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