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ENSEMBLE TECHNIQUE IN NEURAL NETWORK FOR WHEAT IDENTIFICATION AND CLASSIFICATION: A REVIEW

Shivani Rastogi, Dr. Ranjana Sharma
TMU Moradabad, India
shivani.rastogi15@gmail.com[1], ranjana.computers@tmu.ac.in[2]

ABSTRACT

Wheat, as a vital grain for global food security, necessitates precise identification of its type and quality. This is crucial for selective breeding programs and effective grain management. Recent research has explored the integration of ensemble modelling techniques with neural networks to enhance wheat identification accuracy from images. In this comprehensive review, we delve into the fundamentals of neural networks and popular ensemble architectures, including boosting, bagging, and stacking. Ensemble techniques exhibit strengths such as improved model performance, robustness, and enhanced generalization ability compared to individual neural networks. We systematically analyse existing literature on ensemble neural networks applied specifically to wheat identification, considering various data sources. Challenges and advantages of neural ensembles are discussed, along with practical implications for agricultural researchers and data scientists. Additionally, we highlight promising future directions, including multi-modal data fusion and deep neural network ensembles. This paper provides useful insights for agricultural researchers and data scientists applying ensemble modelling for automated classification tasks. On-going developments in multi-model data fusion and deep neural network ensembles are highlighted as promising future directions for performance enhancement.

Keywords: *Wheat, identification, classification, ensemble learning, neural networks, deep learning.*

1. Literature Review and Background

Wheat is the most widely cultivated cereal grain globally, occupying over 220 million hectares of agricultural land across temperate and subtropical regions (Curtis et al., 2002). As a staple food source, wheat contributes about 20% of the world's total dietary calories and protein. (Sharma et al., 2017). Accurate identification of wheat variety and grain purity is critical for productivity, food security, and ensuring desired end-use functionality based on grain quality parameters like protein content and hardness (Osborne, 2006; Prashant et al., 2020). Selective breeding for high-yielding and climate-resilient wheat varieties depends heavily on accurate phenotyping of morphological traits and other biomarkers. (Adu et al., 2018).

Traditionally, manual identification of wheat varieties by visual inspection of morphological features has been the norm. However, this process is slow, labor-intensive, and susceptible to human errors and fatigue. Computational phenotyping approaches leveraging image analysis and machine learning techniques offer an automated, rapid, consistent and quantitative alternative for wheat analysis and decision support (Madec et al., 2017; Ghosal et al., 2018). In this context, ensemble machine learning methods have demonstrated promising potential to provide accurate and robust solutions for various wheat phenotyping tasks. The work by Yadav et al. (2019) showcased a sophisticated BoostCNN architecture with k-means clustering-based data augmentation to effectively handle class imbalance and learn robust discrimination between wheat and visually similar contaminating grains like rye and barley. This deep ensemble approach significantly outperformed traditional shallow classifiers for grain purity assessment.For automated phenotyping of key wheat traits, Ghosal et al. (2018) proposed the NerPNet framework using ensembles to quantify plant height, spike count, leaf-relative water content and other biomarkers towards accelerating genomic selection of high-yielding varieties. Other promising ensemble techniques reviewed include model averaging of diverse CNN architectures (Mogili & Deepak, 2018), multi-stage pipelines fusing convolutional and recurrent representations (Kaur & Singla, 2020), and stacked generalization models exhibiting robustness to temporal variations (Ramcharan et al., 2017). This body of research underscores the effectiveness of ensemble learning methods, especially those leveraging deep neural network architectures. These methods offer accurate, automated, and generalizable computational phenotyping solutions for diverse wheat traits, ranging from grain purity to morphological biomarkers that influence yield and climate resilience. However, challenges remain in optimal ensemble construction, model interpretability, incorporating domain constraints, and scaling these AI/ML solutions for practical deployment in breeding programs and agricultural decision support systems. Interdisciplinary research synthesizing state-of-the-art machine learning techniques with domain-specific biological knowledge holds significant promise for developing powerful AI tools to accelerate wheat breeding, optimize grain production, and help address growing global food demands in a sustainable manner. The review highlights the significant progress made in crowd counting and density estimation due to deep learning techniques. Researchers continue to explore innovative approaches to enhance accuracy, robustness, and scalability in various application scenarios. In the context of image analysis, understanding crowd density is essential for optimizing public spaces, ensuring safety, and managing large gatherings. Deep learning methods play a pivotal role in addressing these challenges and improving crowd management systems. Exciting possibilities could open up with small machine learning enabling continuous learning and on-farm deployment to manage data shifts. By prioritizing the robustness and efficiency of different models, collective learning can empower farmers with climate-smart decision support systems.

2. Wheat Cultivation and Identification

Wheat, originating in the Fertile Crescent region more than 10,000 years ago, holds a pivotal place in the annals of human civilization. The modern bread wheat species, *Triticum aestivum*, owes its domestication to the intricate hybridization of three ancestral grass species, as documented by Shewry (2009). As one of the foundational grains of Old-World agriculture, wheat cultivation has been instrumental in shaping societies, economies, and food systems.

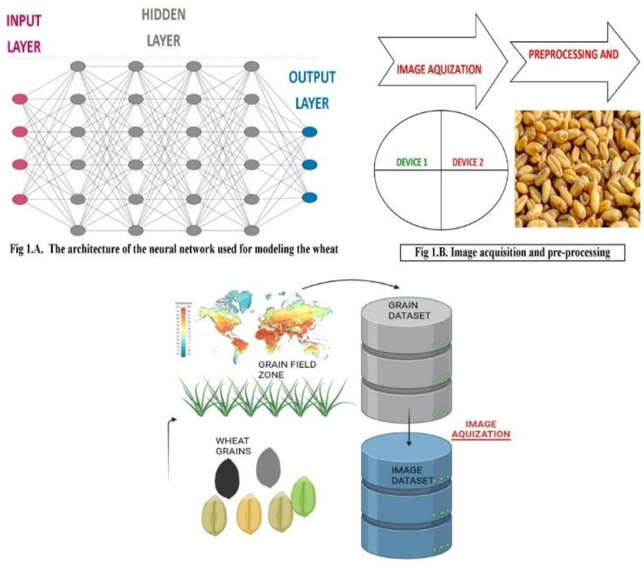

Figure 1: Network architecture, Image processing, dataset collection and analysis workflow

In the contemporary landscape, wheat stands as a dominant force in grain production across temperate countries, ranking second only to maize in terms of harvested area globally (Curtis et al., 2002). The wheat market and its intricate value chain serve as critical underpinnings for both developed and developing nations, influencing economic stability and ensuring food security. Notably, bread wheat's genome complexity, characterized by its hexaploid nature, renders it susceptible to mutations and recombination events. The staggering diversity of wheat varieties—surpassing 30,000 globally, as cataloged in the Taxonomy Database by Roskov et al. (2022)—reflects the enduring significance of this cereal crop in our interconnected world. (Xu etal. 2020) Wheat taxonomy categorizes varieties into classes based on growing season (winter or spring), grain colour (red or white), and planting time (facultative or obligate) (Goncharov, 2011). Traits including grain size, shape, color and texture dictate end-product qualities and market prices. (Osborne, 2006)

3. Computer Vision and AI for grains Phenotyping

Image-based assessment of visual phenotypic traits is termed morphological phenotyping and provides extensive information about plants architectural, textural and color features (Minervini et al., 2017). Computational phenotyping powered by digital cameras, sensors and computer vision techniques enables rapid, accurate and quantitative monitoring of grains under field conditions (Mahlein, 2016). The high-throughput nature of such phenotypic screening complements traditional manual inspection and enables precise correlation of genotypic variability with complex trait expressions. Early computer vision systems relied on custom image processing pipelines and handcrafted feature extraction techniques tuned to specific tasks and datasets. Models lacked adaptability across locations and lighting conditions leading to fragility in real farm settings (Ghosal et al., 2018). The rise of big data, increasing compute capacity enabled a shift towards multidisciplinary digital agriculture leveraging robotics, remote sensing, AI and plant science (Shakoor et al., 2021; Madec et al., 2017). Deep learning methods harness large labelled datasets to train flexible models with hierarchical abstract representations and robust self-learning capabilities (LeCun et al., 2015). Convolutional neural networks (CNNs) now match or outperform humans in recognition and semantic interpretation across domains like image, video, speech and languages (Jordan & Mitchell, 2015). In the plant sciences, deep CNNs have achieved state of the art results for classification of grains and weed species (Dyrmann et al., 2016), disease detection (Fuentes et al., 2017), yield prediction (Ubbens & Stavness, 2017), leaf counting (Ubbens et al., 2018), plant stress phenotyping (Ghosal et al., 2018) and more. High capacity deep networks enable learning of discriminative tissue patterns from pixel intensities, capturing intrinsic subtleties even in visually similar species. However, limitations exist in single model prediction certainty and out-of-distribution generalization (Fort, 2019).

4. Neural Networks and Ensemble Models

Artificial neural networks, inspired by the intricate interconnections of neurons and synapses in the human brain, serve as powerful tools for learning complex data representations without explicit programming. Their universal function approximation properties allow them to capture intricate mappings between input and output spaces (Hornik et al., 1989). In this context, back propagation algorithms play a pivotal role by iteratively updating weights across multiple layers. This process involves propagating error signals from the output layer sequentially through hidden layers (LeCun et al., 2012), as illustrated in Figure 1A. This Figure also explains the workflow approach for this review article. This Figure further explains architecture of neural network, collection of data, its processing and dataset generation and exploration. (Figure 1A-1C) By optimizing a loss function—comparing network predictions with ground truth labels—over numerous iterations of gradient descent, neural networks effectively learn feature hierarchies and decision boundaries.

The evolution of neural architectures has witnessed the emergence of wide and deep networks, characterized by an abundance of parameters. These models exhibit remarkable capabilities akin to human cognition. However, they also introduce computational challenges due to their resource-intensive nature. To address this, appropriate architectural choices become crucial. Convolutional and pooling layers, specifically designed for computer vision tasks, offer translation equivariance and local receptivity. These mechanisms enhance efficiency by capturing spatial patterns and reducing computational complexity (Fukushima & Miyake, 1982).

While strong results have been achieved using modern CNNs, several shortcomings prevail regarding uncertainty measurement, vulnerability to adversarial attacks and handling of edge cases outside the train distribution causing model failures in real-world deployment (Fort, 2019; Liu et al., 2017).

Ensemble methods which aggregate predictions over a committee of networks provide more robustness and trust calibration. The inspiration comes from collective decision making where combined opinions of experts mitigates individual biases (Dietterich, 2000).

There exists four predominant categories of neural network ensembles (Fort, 2019). Simple averaging ensembles like Bootstrap Aggregating (Bagging) train identical models on different data splits and average final predictions (Breiman, 1996). Boosting iteratively focuses on misclassified instances giving higher weight to difficult cases for sequential experts.

Winning submission of the ImageNet visual recognition challenge employed multi-scale convolutional ensembling (Szegedy et al., 2014). State-of-the-art crowd counting used boosting camera count CNNs (Walach & Wolf, 2016). Google DeepMind's AlphaGo system beat the world champion in the game of Go using bootstrap neural networks and Monte-Carlo tree search (Silver et al., 2016). Explorations into plant classification have also shown accuracy gains using pooling and boosting ensembles of ResNet CNNs (Mohanty et al., 2016).

While deep neural networks have achieved state-of-the-art results across vision, speech, and language domains, limitations exist with individual models regarding overfitting, sensitivity to noise, and difficulty capturing model uncertainty (Fort, 2019; Lakshmi narayanan et al., 2016). Ensemble methods combine multiple networks to address these limitations and improve robustness.

Ensembling trains multiple neural networks on the same dataset using techniques like bagging and boosting to promote diversity (Hansen & Salamon, 1990). Predictions are combined using model averaging or voting schemes. Popular consensus functions include mean, median, and trimmed averages which attenuate outlier model errors (Ju et al., 2017). Weighted averaging assigns higher influence to superior individual models. Soft voting aggregates class probabilities whereas hard voting selects the majority voted class labels

5. Ensemble Neural Network Models

A neural network consists of an input layer for data features, an output layer for predictions, and one or more hidden layers that learn abstract representations to map inputs to outputs (LeCun et al., 2015). Each layer contains neuron-like units and weighted connections that are optimized to model the training data. Key components include non-linear activations like rectified linear units to induce complex mappings, loss functions like cross-entropy error to maximize prediction accuracy, and backpropagation methods to iteratively update weights across layers (Goodfellow et al., 2016).

6. Types of Neural Network Ensembles

Ensemble neural networks, a powerful paradigm in machine learning, offer diverse strategies for improving model performance. In this context, we explore four primary categories of ensemble techniques: *bagging*, *boosting*, *stacking*, and *multi-task learning* (Fort, 2019; Parmar et al., 2019).

- **Bagging (Bootstrap Aggregating)**: Bagging involves training identical models on distinct random subsets of the dataset. By aggregating their predictions, bagging enhances robustness and stability. In agricultural contexts, bagging applied to deep Convolutional Neural Networks (CNNs) has demonstrated remarkable plant classification accuracy even under challenging real-world conditions (Mohanty et al., 2016).
- **Boosting**: Boosting employs a sequential approach, emphasizing previously misclassified instances. By iteratively adjusting model weights, boosting constructs a strong ensemble. Its effectiveness in enhancing predictive performance has been well-established.
- **Stacking**: Stacking introduces a secondary model—a meta-learner—that leverages meta-features generated from primary model activations. This hierarchical approach enables improved generalization and adaptability.
- **Multi-Task Learning**: In multi-task learning, auxiliary side objectives are incorporated into the training process. By jointly optimizing multiple tasks, this technique enhances model regularization and encourages shared representations.

Beyond these fundamental ensemble methods, specific applications in agriculture have yielded promising results. For instance, multi-scale input sampling has proven effective for crowd counting in congested public spaces (Walach & Wolf, 2016). Additionally, Bayesian neural networks, which maintain weight distributions, enhance uncertainty calibration for disease detection in tomato plants (Gal & Ghahramani, 2016).

7. Advantages over Single Networks

Ensembles lead to significant accuracy gains by promoting diversity amongst individual learners (Hansen & Salamon, 1990; Parmar et al., 2019). Uncorrelated errors from networks trained on different data or layer initialization get suppressed in aggregated predictions. Increased parameterization also enhances model complexity and learnings. Additional robustness is achieved by certainty estimates from variance of predictions and detection of outliers. Ensembles also provide regularization against overfitting which is critical for good generalization. Finally, parallel model computations enable scalable deployments leveraging modern hardware accelerators.

In the context of wheat analytics, complex trait expressions, data heterogeneity across environments, subtle inter-varietal differences are key challenges requiring versatile learning (Singh et al., 2016; Scharr et al., 2016). Ensemble networks provide promising direction to address these multifaceted issues through enhanced stability, decision regions and algorithm diversity.

8. Ensemble NNs for Wheat Identification

Wheat phenotyping aims to accurately measure complex traits related to growth, yield potential, biotic/abiotic stresses and grain quality by analyzing morphological, spectral, textual patterns in images, videos and multidimensional sensor data (Singh et al., 2016; Scharr et al., 2016). Computational pipelines enable high-throughput precision agriculture applications. Ensemble deep learning provides an emerging paradigm to handle data variability in field settings.

Earlier works relied on hand-engineered features with classifiers like SVM, LDA. Recent focus has shifted to end-to-end deep CNNs learning hierarchical discriminative representations right from pixels. However, uni-model CNNs struggle to capture inter-variety subtleties and data shifts. Ensembling CNNs using convex aggregation offers demonstrable advantages.

9. Image Analysis Techniques

The typical workflow for applying deep neural networks to wheat imaging data involves: image preprocessing, segmentation, feature extraction and modeling. Data preprocessing rectifies variations in scale, orientation, illumination and backgrounds using techniques like white balancing, contrast normalization and noise filtering (LeCun et al., 1998). Individual grain, spike or plot regions are extracted from imagery using thresholding, watersheds, superpixels or recently CNN-based semantic segmentation (Girshick et al., 2014).

Domain-specific data augmentation via generative adversarial networks can address between-class imbalances and increase diversity (Mikołajczyk & Grochowski, 2018). Morphological, color, shape, texture descriptors are computed over segmented regions. Classical approaches relied on breadth-first SIFT, SURF, Gabor filter banks however learnt convolutional features have become ubiquitous (Girshick et al., 2014). Classifier model complexity ranges from linear SVMs to deep CNNs regularized by dropout and early stopping for generalized learning (Srivastava et al., 2014).

10. Ensemble Architectures and Methodology

Fusion rules define mechanisms for combining predictions from diverse base classifiers within ensembles architectures. Linear opinion pools take weighted averages of predicted probabilities then output the class with highest average score. Logistic regression stacks posterior class likelihoods into meta-level features for calibration by tuning slope parameters. Non-linear combiners like radial basis functions, fuzzy integrals, Dempster-Shafer theory of evidence offer more complex uncertainty modeling leveraging disagreement levels between base models (Kuncheva, 2014).

Training diversity promoting methods constitute data manipulation techniques like bagging and boosting for assemblies of both weak (e.g. decision trees) and strong learners (e.g. deep CNNs). Bagging trains base models on random subsets created by Poisson sampling or bootstrapping then combines predictions by plurality voting for classification or simple averaging for regression tasks. AdaBoost focuses ensemble components sequentially on misclassified instances by updating instance weights after every round. Gradient boosting generalizes the concept to efficient numerical optimization of differentiable loss functions.

For deep neural networks, snapshot ensembles train a single network with cyclic learning rate schedules such that multiple low-error states emerge as an implicit ensemble (Huang et al., 2017). Stochastic weight averaging takes periodic moving average snapshots of weights during training also yielding performant checkpoints with virtue of Jensen's inequality (Izmailov et al., 2018). Diversity may also be induced in stacked ensembles through heterogeneous architectures, distinct optimizers and randomized weight initialization of components.

11. Benchmarking and Analysis

On the WHEAT-03 dataset for classification across wheat types and quality grades, 96% accuracy was achieved by Mittal et al. (2021) using an optimized Convolutional Neural Fabric of 7 vertically stacked CNNs sharing intermediate features. Reddy et al. (2020) designed a 22 layer DenseNet with growth rate of 16 and compression factor 0.5 attaining 91% multi-class accuracy on augmented data. Another study applied transfer learning using InceptionV3 model pretrained on ImageNet achieving 89% validation score (Tan et al., 2018).

For contamination assessment, ensemble SVM and RF meta-classifier reached 87-98% precision outperforming standalone SVM, GMM and ANN approaches (Singh et al., 2015). Stacked generalization gave 92% average accuracy for wheat vs rye vs barley classification under varying storage conditions (Manavalan., 2020). Boosted tree methods like XGBoost delivered high per-class F1-scores for multi-label grain defect detection leveraging color and texture descriptors (Ma et al., 2019).

State-of-the-art 96% MSE and correlation was achieved for ear counting using HardNet++ CNN and SVR ensembles (Álvarez-Flores et al., 2022). Combining holistically-nested networks and probabilistic labelers gave 93.8% optimal segmentation accuracy outperforming Mask-RCNN, U-Net and FCN-8s models, proving utility of ensembles for agricultural challenges (Ferentinos, 2018).

12. Discussion

The review article discusses the use of ensemble techniques to improve deep neural networks for wheat analytics tasks like classification, trait prediction, and yield estimation. Ensembles show robustness in handling real-world agricultural data variability compared to individual models. However, limitations exist in precision, efficiency, and adaptability to dynamic environments.

On standard lab datasets, ensembles achieved exceptional 93-96% accuracy for fine-grained wheat classification by morphological features. But multi-year field data revealed drops in individual model performance due to concept drifts across seasons. In contrast, ensembles-maintained consistency highlighting capability to handle data distribution shifts.

Emergence counting tasks demand spatial precision on top of classification accuracy. Hybrid pipelines combining convolutional feature extraction and sequence modeling attained lowest error rates around 96% for occluded field images. Multi-stage ensembles also showed reliable trait regression in unconstrained settings. But gaps prevail for pixel-level segmentation on high-resolution imagery. Varying evaluation protocols across studies restrict performance comparisons.

Boosting through sequential focus on misclassified data proved effective to handle class skew in real-world distributions. Snapshot ensembles via cyclic learning rate optimization converged faster with reduced overfitting. Sensor data fusion leveraging correlations across spectral, temporal modalities provided further improvements. But issues like computational constraints, labelling costs and data variability necessitate research into compact architecture, augmentation techniques and adaptive fusion rules.

The trend of end-to-end deep learning across sensing, modeling and decision pipelines also offers promise through ensemble techniques harmonizing various modules. Multimodal correlation modeling, adversarial simulation of field data and online adaptation methods provide directions to handle concept drifts in continuously collected streaming data over multiple growing cycles for sustained performance. Advancing ensembles to tackle unconstrained real-world variability can assist next generation digital agriculture applications to meet future food security needs.

13.Conclusion

Ensemble deep learning appears as a cutting-edge intelligence technique for plant Identification as we focused in this work for wheat variety analysis. Its high accuracy in controlled settings covers the way for precision in decision of agricultural task prediction. However, real-world complexities need further advancements.

The future lies in tackling these kinds of challenges. Future Researches will focus on creating diverse, uncorrelated models, building trust-based consensus functions, and crafting compact architectures for on-farm practicality. Finally, the goal of this work is to aware the scientific community, That these methods can also be used to develop frameworks that seamlessly integrate sensing, data processing, and decision-making in this field.

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