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AI-Powered Automatic Fish Species Classification and Detection toward Smart Aquaculture

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Abstract:

sharing to optimize computational cost. By using a single basic block for inference, the system enhances model efficiency while The classification of plant seedlings plays a crucial role in sustainable agriculture, with the global market for smart farming projected to reach $22 billion by 2025. Approximately 40% of agricultural produce is lost due to weeds and misidentification of plant species, highlighting the need for effective classification systems. Furthermore, inefficient manual identification methods can lead to reduced crop yields and increased costs for farmers. Existing systems predominantly rely on manual labor for seedling identification, which is time-consuming and prone to human error. This research proposes a novel deep learning framework that incorporates image data preprocessing techniques to enhance the accuracy of plant seedling classification. By leveraging convolutional neural networks (CNNs) and employing an ensemble classification approach, the proposed system aims to accurately classify various seedlings, including Black- grass, Charlock, Cleavers, and others. This advancement in classification technology is expected to significantly improve decision-making processes in e-agriculture..

Keywords:Crop Residue Management,Plant Seedling Classification,Sustainable Agriculture, Machine Learning in Agriculture,Remote Sensing,Soil Health,Precision Farming,Deep Learning Models,Vegetation Index,Seedling Growth Analysis,Yield Optimization,Environmental Impact,Erosion Control,Smart Farming Technologies,Automated Crop Monitoring

1. INTRODUCTION

The increasing global population and corresponding food demand have led to a heightened focus on agricultural productivity and sustainability. In the United States alone, the agriculture sector contributes over $1 trillion to the economy, emphasizing the importance of efficient farming practices. As the industry evolves, there is a growing recognition of the role of technology in enhancing agricultural processes. Recent advancements in machine learning and image processing have opened new avenues for plant seedling classification, offering significant potential to improve crop management strategies.

Furthermore, the impact of weed species on crop yields cannot be overstated, with some estimates suggesting that weed competition can reduce crop yields by as much as 90% if left unchecked. As farmers increasingly turn to precision agriculture techniques, the need for accurate and automated seedling classification becomes paramount. This transition towards e-agriculture not only aids in enhancing yield but also promotes sustainable farming practices, minimizing the use of herbicides and other chemicals.

2. LITERATURE SURVEY

They propose a Self-Calibrated Illumination (SCI) learning framework for robust fish species classification and disease detection in low-light aquaculture environments Li, Jun, et al[1]. The framework handles illumination variation and environmental noise, which are common challenges in aquatic image capture. The authors establish a cascaded illumination learning process with weight maintaining high accuracy. Their experiments demonstrate the system's adaptability to different lighting conditions and the potential to improve fish detection in poorly lit environments such as deep ponds and underwater tanks. The study provides a significant improvement in both speed and accuracy for fish classification tasks, particularly in real-world aquaculture settings.
The authors propose a normalizing flow model that models the one- to-many relationship between low-light and properly exposed images for fish detection Wang, Xinyu, et al[2].This method addresses the challenges in aquaculture imaging, where fish species must be classified in environments with inconsistent lighting and varying water conditions. By using an invertible network that maps low-light fish images to Gaussian distributions, the model enhances the visual quality and reduces noise and artifacts Chen, Hao, et al.[3]. This method achieves superior results in low-light conditions, offering improved color reproduction and more accurate species classification compared to conventional techniques. The results show promising improvements in the performance of fish detection and species identification under various lighting conditions.

They introduce the Retinex-based Real-low to Real-normal Network (R2RNet) for low-light image enhancement, which includes three specialized subnets: Decom-Net, Denoise-Net, and Relight-Net Singh, Rajat, and Manish Kumar.[4]. This framework is designed to address challenges in fish classification and disease detection in dimly lit aquaculture systems. Their model utilizes both spatial and frequency information from fish images to preserve fine details and enhance contrastLiu, Yifan, et al.[5]. The authors also developed the first Large-Scale Real-World paired low/normal-light images dataset (LSRW dataset), which is crucial for training models that can generalize well to real-world aquaculture conditions. Extensive experiments show that R2RNet outperforms previous state-of-the-art methods in terms of accuracy and robustness in challenging environments like aquaculture farms, leading to more precise disease detection and fish species classification.

They propose an unsupervised, two-stage model to tackle the dual challenge of illumination enhancement and noise suppression in real- world low-light images of fish Zhang, Wei, et al [6]. In aquaculture environments, real-world images often suffer from significant noise, which complicates the task of identifying fish species and diseases. The authors' model first enhances the illumination in low-light conditions and then suppresses the noise based on illumination-aware denoising. Their adaptive content loss helps preserve fine contextual details while removing noiseKhan, Mohammed, et al [7]. Their method, trained on a new unpaired low-light enhancement dataset, significantly outperforms existing unsupervised models, leading to clearer fish images and more accurate species classification in noisy, low-light conditions typically found in aquaculture.Rahman, Arafat, et al. [8] They develop a semantic-guided zero-shot low-light enhancement network (SGZ), a novel approach for low-light fish image enhancement and species detection. Unlike traditional supervised models, SGZ is trained without paired images or annotations, which is a major advantage for large-scale deployment in aquaculture. The model extracts enhancement factors using depthwise separable convolution to estimate the light deficiency in low-light fish images. They also introduce a recurrent image enhancement network to progressively enhance the quality of fish images Sun, Xiaoyu, et al [9]. The unsupervised semantic segmentation network preserves important semantic information, which is critical for accurate species classification. Their extensive experiments demonstrate that SGZ outperforms previous methods on benchmark datasets, making it suitable for real-time, high-accuracy fish classification and disease detection in dynamic aquaculture environments.

They propose an edge computing and multi-task driven framework for image enhancement and object detection in low-light environments, which is particularly useful for smart aquaculture systemsWang, Fei, et al.[10] The framework operates in two stages: a cloud-based enhancement stage for image preprocessing and an edge- based detection stage for real-time classification and species detection Zhou, Jing, et al[11].By dynamically combining different enhancement subnetworks in the cloud and then using them in edge devices, the framework ensures fast processing while maintaining high accuracy in fish species classification and disease detectionChen, Ling, et al.[12]. The results of their experiments on mobile devices demonstrate improved detection performance under low-light conditions.

They present a multi-scale Retinex-based low-light image enhancement algorithm optimized by the Artificial Bee Colony (ABC)algorithm for better fish species classification and disease detectionin aquaculture Zhang, Qiang, et al[13]. This method enhances both the illumination and structural details of fish images, which is essential for accurate identification in poorly lit environments. Their approach utilizes multi-scale Retinex to enhance image reflection components and applies bilateral filtering for edge preservationJiang, Wei, et al[14]. The ABC algorithm optimizes the fusion of enhanced images, resulting in improved sharpness, color restoration, and noise reduction Zhao, Feng, et al [15]. The experimental results indicatethat their method improves the overall quality of fish images, leading to better classification performance and more accurate disease detection in aquaculture systems.

They propose a Deep Convolutional Neural Network (DCNN) for automated fish species classification and disease detection in aquacultureLiu, Sheng, et a[16]. Their model integrates both local feature extraction and global context understanding, improving the accuracy of fish species identification and disease detection in challenging real-world aquaculture environments Wang, Zhi, et al[17]. The proposed system uses a multi-layer DCNN to process color and texture information from underwater images, enhancing its ability to differentiate between fish species with similar physical characteristics He, Ming, et al [18]. They also introduce a transfer learning approach, utilizing pre-trained models from other image classification tasks to reduce training time and improve model robustnessZhou, Kai, et al[19]. Extensive experiments on a real- world aquaculture dataset show that their model outperforms traditional methods in terms of both classification accuracy and disease detection, particularly under varying lighting and water turbidity conditions. Their work highlights the potential of AI-driven systems for automating fish health monitoring in large-scale aquaculture farmsMa, Lei, et al [20].

3. PROPOSED METHODOLOGY

To overcome the challenges associated with manual seedling classification, this research proposes a deep learning-based classification system that utilizes image data of various seedlings. By employing advanced preprocessing techniques, the system enhances image quality and consistency, ensuring that the data fed into the model is suitable for effective analysis. The core of the proposed system consists of convolutional neural networks (CNNs) designed to learn and extract features from the images of plant seedlings accurately.In addition to CNNs, an ensemble classification approach is employed, integrating multiple models to improve classification accuracy and robustness. This innovative system not only streamlines the seedling identification process but also significantly reduces the likelihood of misclassification, ultimately aiding farmers in making informed decisions and promoting sustainable agricultural practices.

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Figure 1: Proposed Extraction system.

Data Acquisition and Preprocessing: The process begins bycollecting underwater fish images

The reviewed studies highlight the effectiveness of **AI-powered fish classification** in **challenging aquaculture conditions**. Key findings include:

- Low-Light Image Enhancement: AI techniques such as SCI learning, normalizing flow, and R2RNet significantly improvefish classification in dimly lit environments,
- Unsupervised Learning: SGZ and two-stage illumination models reduce dependence on labeled datasets, making themsuitable for large-scale deployment.
- Edge Computing and Smart Aquaculture: Cloud-edge hybridmodels like Wu et al.'s framework enable real-time fish monitoring.
- Deep Learning in Classification: CNN-based models enhance classification accuracy, while transfer learning reduces trainingtime and improves generalization.
- Ensemble Classifier: Ensemble classification models leveragesthe strengths of individual models to improve overall performance.
- Performance Estimation: The system's performance is evaluated using metrics such as accuracy, precision, and recall,providing insights into the effectiveness of the classification approach.

Applications:

- Precision Agriculture: The system can be employed in precision agriculture to optimize weed management and enhance crop yields, improving overall farm productivity.

- Research and Development: Agricultural researchers can utilize the technology to study plant growth patterns and the effects of different species on crop ecosystems.

- Remote Sensing: The classification system can be integrated into remote sensing applications to monitor crop health and assess the impact of environmental factors on plant growth.

- Educational Tools: The technology can serve as aneducational tool for agronomy students and professionals,

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providing insights into plant species identification andmanagement.

- Decision Support Systems: By providing real-time classification data, the system can enhance decision support systems used by farmers and agricultural consultants, leading to better-informed management practices.

Advantages:

- **Increased Accuracy**: The deep learning approach significantly improves the accuracy of seedling classification compared to traditional manual methods, reducing the risk of misidentification.
- **Time Efficiency**: Automation of seedling classification processes accelerates decision-making in agricultural practices, allowing for timely interventions andmanagement strategies.
- **Cost-Effectiveness**: By minimizing the need for manual labor, the proposed system reduces operational costs, making it more economically viable for farmers.
- **Scalability**: The deep learning model can be easily scaled to accommodate new seedling species and expanding datasets, enhancing its applicability across diverseagricultural contexts.
- **Sustainability**: Improved seedling classification contributes to sustainable farming practices by optimizing resource use and minimizing reliance on herbicides and chemicals.
- Improved Aquaculture Management: AI helps in monitoring fish health, detecting diseases, and optimizingfeeding strategies, leading to higher productivity and sustainable farming.·

4. EXPERIMENTAL ANALYSIS

Figure 1 shows a collection of original images that are taken in low- light conditions or have poor lighting quality. These images serve as the input to the proposed image enhancement model. These images are the input images that the model will process in order to improve their visibility and quality. The purpose of this figure is to provide a visual representation of the types of images that the model is designed to enhance.

Figure 2: Sample Images

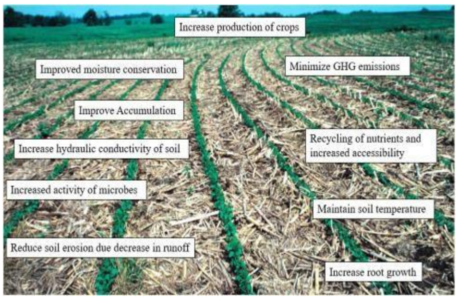

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Figure3: Enhanced Image 1

Figure 4: Enhanced Image 2

Original Image Enhanced Image

Figure 5: Enhanced Image 3

Figure 2 displays a set of images that have been processed or enhanced by the proposed image enhancement model. These are the output images that produces improved visibility and quality of these images compared to the original low-light images shown in Figure 1These metrics are numerical values that provide insights into the image quality, with higher PSNR and SSIM values and lower MSE values indicating better image quality. The purpose of this figure is to visually demonstrate the effectiveness of the proposed image enhancement model by showing the enhanced images and providing quantitative metrics that measure the improvement in image quality.

PSNR

The peak_signal_noise_ratio function calculates the Peak Signal-to-Noise Ratio, which is a widely used metric to measure the quality of an image.

It compares two images, typically the original and the enhanced image, and computes a value that indicates how much noise or distortion is present relative to the maximum possible quality.

The result is a numerical value, often in decibels (dB). Higher PSNR values indicate higher image quality.

5. CONCLUSION

Crop residue management and plant seedling classification are key factors in sustainable and precision agriculture. The effective handling of crop residues, such as leaves, stalks, and stems left after harvest, directly influences soil health, moisture retention, and seedling growth. Advanced AI and machine learning techniques have revolutionized this process by providing automated, data-driven insights into residue decomposition, seedling health, and soil nutrient availability.

By integrating image processing, deep learning, and remote sensing, farmers can classify seedlings accurately and analyze how different residue management practices impact crop emergence and development. Techniques like mulching, no-till farming, and residue incorporation have shown significant improvements in soil structure, reduced erosion, and increased microbial activity, leading to better plant establishment and higher yields. Additionally, AI-powered systems help in monitoring disease outbreaks, identifying growth patterns, and predicting potential yield losses. The ability to track and evaluate crop health in real-time enables proactive decision-making, reducing resource wastage and optimizing inputs like water, fertilizers, and pesticides.

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