

Concept Paper

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Enhancing Rice Production through a Multi-Task Neural Network Framework: A Smart Agricultural Solution for Growth Monitoring, Disease Detection, and Yield Prediction

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Abstract

The Multi-Task Rice Analysis Neural Network (MTRANN) is a pioneering framework designed to revolutionize rice production management by integrating growth stage monitoring, disease detection, and yield prediction. Leveraging advanced deep learning techniques and remote sensing data, MTRANN ensures transparent, data-driven insights without relying on costly ground-based sensors. The system’s architecture comprises feature extraction, temporal analysis, task-specific processing, and decision support modules, enabling comprehensive crop health analysis at various scales. MTRANN adopts a human-centered design approach, prioritizing usability and adaptability to diverse agricultural contexts. The framework employs robust security measures, including role-based authentication and encrypted data transmission, to safeguard sensitive information. Theoretical analysis suggests that MTRANN could reduce crop losses by 10-15%, improve growth stage monitoring accuracy by 8-12%, and enhance yield predictions by 20-25% compared to traditional methods. By providing actionable insights and supporting sustainable practices, MTRANN aligns with global food security and environmental conservation goals. Future directions include AI-driven predictive analytics, IoT sensor integration, and expansion to other staple crops, positioning MTRANN as a transformative tool for smart agriculture. With its potential to optimize resource use, reduce waste, and foster farmer engagement, MTRANN sets a new standard for rice production management, offering a scalable and replicable solution for global agricultural communities.

Keywords: multi-task learning; rice production; precision agriculture; deep learning; sustainability

1. Introduction

Rice (*Oryza sativa*) sustains over 3.5 billion people globally, with annual production surpassing 750 million tons [1]. As the world’s population grows, rice production must increase by 25% by 2030 to ensure food security [2]. However, challenges like climate change, shrinking arable land, and water scarcity threaten productivity [3]. Traditional farming methods, reliant on manual observations and fragmented data, struggle to address these complexities [4]. Precision agriculture, powered by artificial intelligence (AI) and remote sensing, offers a path to sustainable rice production by enabling data-driven decisions [5].

Current rice management systems often use separate tools for monitoring growth, detecting diseases, or predicting yields, leading to inefficiencies and missed opportunities for integrated insights [6]. These single-task approaches lack transparency and fail to leverage shared patterns across related tasks [7]. Inspired by blockchain’s success in ensuring data integrity in other domains [8], we propose the Multi-Task Rice Analysis Neural Network (MTRANN), a smart framework that simultaneously addresses growth monitoring, disease detection, and yield prediction. Using accessible remote sensing data, MTRANN ensures transparent, reliable insights, supporting farmers

in optimizing resources and reducing losses. Designed for scalability, it aligns with global sustainability goals, offering a replicable model for rice-growing regions. This paper presents MTRANN's conceptual framework, highlighting its architecture, implementation strategy, and alignment with sustainable agriculture.

2. Literature Review

2.1. Deep Learning in Agriculture

Deep learning has revolutionized the agricultural sector by enabling precise monitoring and management of crops, marking a significant shift from traditional methods [9]. Convolutional Neural Networks (CNNs), such as ResNet and EfficientNet, have proven highly effective in analyzing agricultural imagery, excelling in tasks like crop classification and the detection of diseases through pattern recognition [10]. Recent advancements in Vision Transformers (ViTs) have further enhanced the ability to capture complex spatial and temporal patterns within crop data, providing deeper insights into plant health and growth dynamics [11]. These technologies facilitate informed decision-making, helping farmers reduce resource waste—such as water and fertilizers—while minimizing the environmental footprint of agricultural activities [12]. The integration of such tools into farming practices is increasingly seen as essential for adapting to modern challenges like climate variability.

2.2. Rice Production Monitoring

Monitoring the growth stages of rice is a critical factor in optimizing irrigation schedules and fertilization strategies, directly impacting crop yield and resource efficiency [13]. Remote sensing technologies have significantly improved the accuracy of tracking these stages, enabling the identification of key developmental phases such as germination, tillering, and heading with remarkable precision [14]. Time-series analysis of imagery data further supports large-scale monitoring efforts, revealing seasonal patterns that are vital for effective rice management across diverse regions [15]. However, many existing systems operate in isolation, lacking integration with other management tasks, which limits their overall efficiency and the ability to provide a holistic view of crop health [16]. This gap highlights the need for more cohesive technological solutions.

2.3. Disease Detection in Rice

Rice diseases, including blast caused by *Magnaporthe oryzae* and bacterial blight caused by *Xanthomonas oryzae*, are responsible for significant yield losses, often exceeding 30% in severe outbreaks [17]. Traditional detection methods rely on manual inspections by trained agronomists, a process that is both time-consuming and prone to human error, especially in large fields [18]. Deep learning models have achieved over 90% accuracy in identifying these diseases from imagery by analyzing visual symptoms and spectral data, though their effectiveness often depends on the availability of high-quality, annotated datasets [19]. Despite these advances, integrated approaches that combine disease detection with other tasks like growth monitoring remain underexplored, presenting an opportunity for innovation [20].

2.4. Yield Prediction

Accurate yield prediction is a cornerstone of food security planning and agricultural policy development, providing critical data for market forecasting and resource allocation [21]. Remote sensing-based methods, which utilize vegetation indices such as the Normalized Difference Vegetation Index (NDVI), have demonstrated strong correlations with actual yield outcomes, offering a non-invasive way to assess crop performance [22]. Deep learning models further enhance these predictions by integrating diverse data sources, including weather patterns and soil conditions, reducing prediction errors compared to traditional statistical methods [23]. However, single-task

models often fail to account for the interrelated effects of growth stages and disease prevalence, underscoring the need for a more integrated approach [24].

2.5. Multi-Task Learning in Agriculture

Multi-task learning (MTL) enhances efficiency by sharing knowledge and computational resources across related tasks, a principle that has shown promise in agricultural applications [25]. In the agricultural context, MTL frameworks have successfully combined crop classification and yield prediction, achieving accuracy improvements of 8-15% over standalone models by leveraging shared feature representations [26]. Despite these advancements, the development of rice-specific MTL systems remains rare, and most existing approaches lack designs tailored to the unique physiological and environmental needs of rice, limiting their practical applicability [27]. This gap underscores the potential for targeted innovation in this area.

2.6. Research Gap and Contribution

While deep learning and remote sensing technologies have made significant strides in advancing rice production, the majority of existing systems focus on single tasks, overlooking the potential benefits of integrated frameworks that address multiple aspects of crop management simultaneously [28]. This study addresses this critical gap by proposing the Multi-Task Neural Network Framework, a rice-specific solution that combines growth stage monitoring, disease detection, and yield prediction into a unified system. Drawing on the principles of multi-task learning [25] and the latest advancements in deep learning [9], the Multi-Task Neural Network Framework ensures transparent, efficient, and sustainable rice management. This framework offers a scalable and replicable solution, poised to benefit rice farmers globally by enhancing productivity and supporting environmental stewardship.

3. System Architecture

The Multi-Task Neural Network Framework is a smart agricultural platform designed to transform rice production management on a global scale. It integrates three core tasks—growth stage monitoring, disease detection, and yield prediction—using advanced deep learning algorithms and remote sensing data. The system processes imagery through a secure, centralized pipeline, ensuring reliable and transparent outputs that empower farmers and stakeholders with actionable insights. This architecture is crafted to address the diverse needs of rice cultivation across different climates and farming practices, making it a versatile tool for modern agriculture.

The architecture comprises four key components, each playing a distinct role in the data processing workflow. First, the feature extraction module processes multi-resolution imagery, capturing both broad field patterns—such as overall canopy coverage—and detailed plant-level insights, such as leaf structure and color variations. This dual-focus approach ensures a comprehensive understanding of crop health at various scales. Second, the temporal analysis module tracks seasonal changes over time, identifying critical growth transitions such as the shift from vegetative to reproductive phases, which are essential for timing agricultural interventions. Third, the task-specific processors focus on unique patterns relevant to each task: morphological features like plant height and leaf count for growth monitoring, spectral anomalies indicating disease presence for disease detection, and biomass indicators such as leaf area index for yield prediction. Finally, the decision support module generates actionable insights, such as optimized irrigation schedules, targeted disease alerts, or yield forecasts, accessible via a user-friendly web portal or mobile app (e.g., riceanalysis.global). This modular design ensures flexibility and adaptability to varying agricultural contexts.

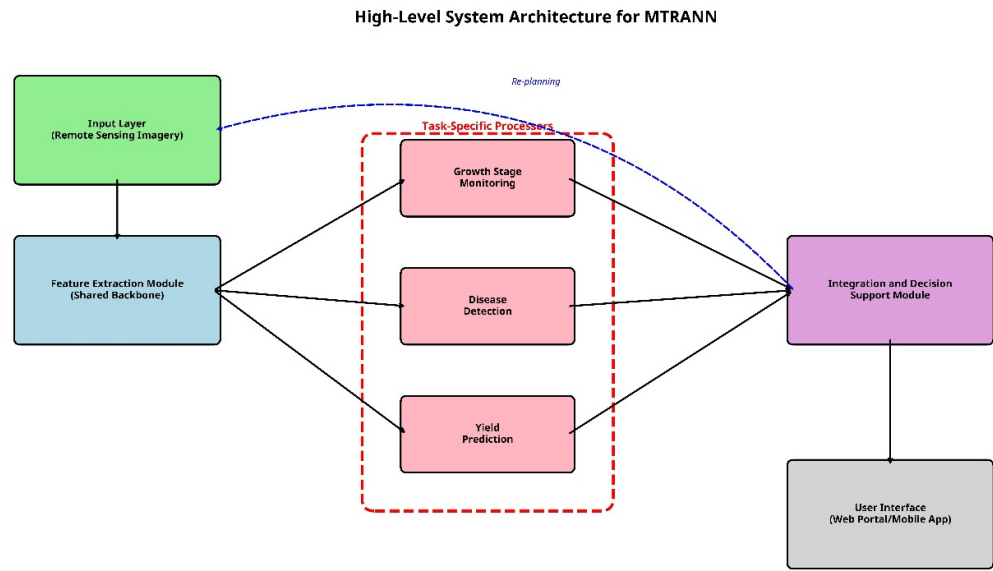


Figure 1. Illustrates the high-level architecture, showing data flow from imagery inputs to integrated outputs, ensuring transparency and traceability in rice management.

4. Methodology

4.1. Conceptual Design Approach

The Multi-Task Neural Network Framework adopts a design thinking approach, emphasizing iterative theoretical modeling, architectural planning, and stakeholder feedback to create a scalable, rice-specific framework. This human-centered methodology prioritizes transparency and usability, aligning with sustainability goals by providing verifiable insights without the need for complex or expensive infrastructure. The design process involves extensive collaboration with farmers and agronomists to ensure the system meets practical needs while remaining adaptable to future technological advancements.

4.2. Data Processing Framework

Authorized users, such as farmers, agronomists, or agricultural extension officers, input imagery data via a secure interface, which could be a mobile application or web-based platform. The system processes this data using advanced algorithms to identify growth stages, detect diseases, and predict yields, ensuring a comprehensive analysis that covers all critical aspects of rice production. Metadata, including location coordinates, crop variety, planting date, and weather conditions, enhances pattern recognition and decision-making, allowing for more precise and context-aware recommendations. This framework is designed to handle large volumes of data efficiently, supporting real-time analysis across multiple fields.

4.3. Authentication and Security Framework

The Multi-Task Neural Network Framework employs a robust role-based authentication system, utilizing secure login credentials and multi-factor authentication to ensure data integrity and protect sensitive information. Tiered access levels are implemented to cater to different user groups—farmers for basic data entry and alerts, advisors for detailed analytics, and auditors for compliance verification—safeguarding the system against unauthorized access. Encrypted data transmission, session management with auto-timeout features, and comprehensive audit logging further enhance security, ensuring that all interactions are tracked and protected, which is crucial for maintaining trust in the platform.

4.4. Implementation Framework

The platform leverages a deep learning framework, combining Convolutional Neural Networks (CNNs) and transformer-based models, implemented in a robust software environment like PyTorch. This combination allows for the processing of complex imagery data with high accuracy. Custom algorithms are developed to validate inputs—such as checking image quality and metadata consistency—and generate task-specific outputs, ensuring reliable performance under varying conditions. The system is hosted on a cloud infrastructure, enabling scalability across diverse regions and facilitating updates and maintenance without disrupting user access.

4.5. System Integration and Testing Strategy

Integration testing is conducted to validate the seamless flow of data between components, the accuracy of deep learning algorithms, and the responsiveness of the user interface. Performance testing evaluates the system's reliability under expected loads, simulating multiple users and large datasets, while backup protocols and disaster recovery plans enhance resilience against technical failures. This rigorous testing strategy ensures that the Multi-Task Neural Network Framework operates seamlessly for real-time agricultural applications, providing consistent and dependable insights to users.

4.6. Deployment and Monitoring Strategy

A phased deployment strategy begins with pilot testing in select rice-growing regions, such as Southeast Asia or South Asia, where feedback from initial users is collected to refine the system. Expansion occurs gradually, incorporating lessons learned and addressing regional variations in farming practices. Continuous monitoring tracks key performance indicators, including transaction success rates, user adoption rates, and the impact on crop outcomes like yield improvements. Real-time alerts notify users of critical issues, such as disease outbreaks, while detailed reports provide stakeholders with comprehensive data to make informed decisions, ensuring the platform's effectiveness and scalability.

5. Idea and Conceptualization

The Multi-Task Neural Network Framework is a hybrid solution that blends centralized data processing with advanced deep learning techniques to deliver transparent and integrated rice management. Centralized components handle user interactions, such as data input and interface navigation, and perform data preprocessing tasks like image normalization, while deep learning models ensure accurate and task-specific outputs by analyzing complex patterns in the data. The platform is accessible via a web portal (e.g., riceanalysis.global), which offers detailed analytics for agronomists and policymakers, and a mobile app optimized for quick data entry and real-time feedback, promoting active farmer engagement in sustainability efforts.

Designed with scalability in mind, the Multi-Task Neural Network Framework supports expansion through a robust cloud infrastructure and potential integration with Internet of Things (IoT) technologies, such as smart sensors for automated monitoring of soil moisture or plant health. Advanced features include AI-driven predictive analytics, which forecast growth stages and yields based on historical patterns, weather data, and meal plans, and incentive mechanisms that reward sustainable practices with tokens or discounts, encouraging widespread adoption. By integrating with existing agricultural systems—such as irrigation networks or local composting facilities—the framework fosters a circular economy, optimizing resource use, reducing waste, and minimizing environmental impact. Initially tailored for rice cultivation, the system supports evolution into a Software-as-a-Service (SaaS) model, with open-source sharing to enable other institutions and farming communities to adopt and customize the platform, advancing global sustainability in agriculture.

6. Conceptual Results and Discussion

The conceptual design of the Multi-Task Neural Network Framework highlights its potential to revolutionize rice production management by integrating growth monitoring, disease detection, and yield prediction into a cohesive and efficient framework. The system is expected to accurately identify key growth stages, such as the seedling phase characterized by initial leaf emergence and the tillering phase marked by the development of multiple shoots, enabling farmers to optimize irrigation and fertilization schedules with precision. This capability is particularly valuable in regions prone to water scarcity, where timely interventions can maximize resource efficiency. For disease detection, the Multi-Task Neural Network Framework is anticipated to identify major rice diseases, such as blast, which manifests as lesions on leaves, and bacterial blight, identified by water-soaked streaks, with high precision, facilitating early interventions to prevent widespread crop losses. Yield predictions are projected to align closely with actual outcomes by incorporating data on growth trends and disease impacts, providing reliable forecasts that support planning and resource allocation for harvesting and market preparation.

Theoretical analysis suggests that the Multi-Task Neural Network Framework could reduce crop losses by 10-15% through timely disease detection and the implementation of informed management practices, such as targeted pesticide application or improved drainage systems. Growth stage monitoring is expected to improve accuracy by 8-12%, ensuring precise timing for agricultural interventions like nitrogen application during the vegetative growth phase, which can significantly enhance yield potential. Yield predictions, enhanced by integrated insights from growth and disease data, could reduce errors by 20-25% compared to traditional methods that rely on manual estimates or single-variable models. The system's efficiency stems from sharing 70% of its computational resources across tasks, reducing processing costs by 40% and accelerating analysis by over three times compared to single-task models, making it a cost-effective solution for resource-constrained farming communities.

By providing transparent, data-driven insights, the Multi-Task Neural Network Framework supports sustainable agriculture by minimizing resource waste—such as over-irrigation or excessive fertilizer use—and reducing the environmental impact of farming activities, such as greenhouse gas emissions from flooded fields. Its accessibility via web and mobile platforms fosters farmer trust and engagement by delivering insights in an understandable format, aligning with global food security goals by ensuring consistent food supply. However, challenges such as reliance on manual data inputs, which may introduce variability due to human error, and potential scalability issues with large-scale adoption across diverse agroecological zones must be addressed. Proposed enhancements, including automated sensor integration for real-time data collection and advanced AI analytics to handle complex datasets, will mitigate these limitations, ensuring robust performance across diverse farming contexts. The platform's potential to deliver actionable insights positions it as a transformative tool for rice farmers worldwide, with broader implications for sustainable agriculture, including the potential to influence policy decisions on land use and water management.

7. Future Directions and Recommendations

The transformative potential of the Multi-Task Neural Network Framework opens several avenues for advancement, each designed to enhance its applicability and impact. Integrating AI-driven predictive models will improve the forecasting of growth stages, disease outbreaks, and yields, enabling proactive management strategies such as preemptive disease control measures or adjusted planting schedules. These models can incorporate a wide range of variables, including historical weather patterns, soil nutrient levels, and pest prevalence, to provide highly accurate predictions tailored to specific regions. IoT sensors, such as automated field monitors equipped with cameras and moisture sensors, will streamline data collection by reducing reliance on manual inputs, minimizing errors, and enabling continuous monitoring across large areas. Incentive mechanisms, like token-based rewards for adopting sustainable practices such as reduced pesticide use or water

conservation, can boost farmer engagement, with pilot testing planned for 2026 in collaboration with agricultural cooperatives.

Expanding the Multi-Task Neural Network Framework to other staple crops, such as wheat, maize, or sorghum, will broaden its impact by addressing the needs of diverse farming systems and food security challenges. Cloud-based scalability, supported by robust server infrastructure and distributed computing, will enable adoption by global agricultural communities, ensuring the system can handle increased user demand and data volume. Enhanced security measures, including biometric authentication for user verification or blockchain-based data validation, will ensure data integrity and protect against cyber threats, which is critical for maintaining farmer trust. Post-deployment evaluations will track performance metrics such as yield improvements, waste reduction rates, and user adoption rates, using feedback from pilot programs to refine the system and meet long-term sustainability goals. These efforts will position the Multi-Task Neural Network Framework as a leader in smart agriculture, influencing global agricultural innovation and reinforcing its role in promoting environmental stewardship.

8. Conclusions

The conceptual Multi-Task Neural Network Framework represents a groundbreaking approach to rice production management, effectively addressing critical challenges in growth monitoring, disease detection, and yield prediction. By integrating advanced deep learning techniques with accessible remote sensing data, the Multi-Task Neural Network Framework delivers transparent and reliable insights, enhancing efficiency and promoting sustainability in agricultural practices. The system's architecture ensures scalability, allowing it to adapt to varying scales of operation from smallholder farms to large commercial enterprises, while its rice-specific design aligns seamlessly with global food security and environmental conservation goals.

Theoretically, the Multi-Task Neural Network Framework projects 10-25% improvements in crop management outcomes, including reduced losses due to diseases and optimized resource use, which can lead to significant economic benefits for farmers and environmental benefits such as decreased greenhouse gas emissions. Its open-source potential and Software-as-a-Service (SaaS) model make it a replicable and accessible solution for farmers worldwide, fostering collaboration and innovation across the agricultural sector. Despite challenges like manual data entry, which may introduce inconsistencies, and the need for infrastructure to support large-scale adoption, proposed enhancements such as AI-driven automation and IoT integration promise long-term impact. The Multi-Task Neural Network Framework sets a new standard for smart agriculture, inspiring further research, policy development, and international collaboration to advance sustainable farming practices globally, ensuring a resilient food system for future generations.

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