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ENHANCING CROP HEALTH THROUGH DIGITAL TWIN FOR DISEASE MONITORING AND NUTRIENT BALANCE

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Abstract. *Digital twins is a digital replica of a physical object to observe its real-time performance, gather data, and recommend corrective actions if required to enhance its performance. This fascinating technological idea is now reaching the agriculture fields to transform farming, by creating digital twins of entire farms. This initiative presents an innovative strategy to enhance crop health and yield by creating a digital twin for paddy fields. The aim is to enable early detection of nutrient deficiencies and leaf blast disease, leading to a transformation in agriculture. Creating virtual replicas of plants and fields, the digital twin harnesses real-time data and advanced analytics to transform the way agricultural systems are managed. By integrating remote sensing, data analytics, and various Internet of Things devices like pH, nitrous, potassium, and phosphorus sensors, coupled with a gateway system, the digital twin provides real-time monitoring and analysis of crop health and nutrient levels. Employing advanced machine learning algorithms, notably Convolutional Neural Networks ensures precise and early detection of nutrient deficiencies and crop diseases. This ground-breaking technology provides timely alerts and actionable insights to farmers, enabling proactive decision-making for optimal crop management. This farmland digital twin represents a transformative approach towards agricultural sustainability and enhancing productivity.*

Keywords: agricultural sustainability, convolution neural networks, digital twin, internet of things, nutrient deficiency detection

POPRAWA ZDROWIA UPRAW ZA POMOCĄ CYFROWEGO BLIŹNIAKA DO MONITOROWANIA CHORÓB I BILANSU SKŁADNIKÓW ODŻYWCZYCH

Streszczenie. *Cyfrowe bliźniaki to cyfrowa replika obiektu fizycznego, która umożliwia obserwację jego działania w czasie rzeczywistym, gromadzenie danych i rekomendowanie działań naprawczych, jeśli jest to wymagane w celu poprawy jego wydajności. Ta fascynująca koncepcja technologiczna dociera obecnie do dziedzin rolnictwa, aby przekształcić rolnictwo, tworząc cyfrowe bliźniaki całych gospodarstw. Inicjatywa ta przedstawia innowacyjną strategię mającą na celu poprawę zdrowia i plonów upraw poprzez stworzenie cyfrowego bliźniaka pól ryżowych. Celem jest umożliwienie wczesnego wykrywania niedoborów składników odżywczych i zarazy liści, co doprowadzi do transformacji rolnictwa. Tworząc wirtualne repliki roślin i pól, cyfrowy bliźniak wykorzystuje dane w czasie rzeczywistym i zaawansowane analizy, aby zmienić sposób zarządzania systemami rolniczymi. Dzięki integracji teledetekcji, analizy danych i różnych urządzeń Internetu rzeczy, takich jak czujniki pH, azotu, potasu i fosforu, w połączeniu z systemem bramek, cyfrowy bliźniak zapewnia monitorowanie i analizę stanu upraw i poziomów składników odżywczych w czasie rzeczywistym. Zastosowanie zaawansowanych algorytmów uczenia maszynowego, w szczególności konwolucyjnych sieci neuronowych, zapewnia precyzyjne i wczesne wykrywanie niedoborów składników odżywczych i chorób upraw. Ta przełomowa technologia zapewnia rolnikom aktualne alerty i przydatne informacje, umożliwiając proaktywne podejmowanie decyzji w celu optymalnego zarządzania uprawami. Ten cyfrowy bliźniak pól uprawnych reprezentuje transformacyjne podejście do zrównoważonego rozwoju rolnictwa i zwiększania produktywności.*

Słowa kluczowe: zrównoważony rozwój rolnictwa, konwolucyjne sieci neuronowe, cyfrowy bliźniak, internet rzeczy, wykrywanie niedoboru składników odżywczych

Introduction

The need for food and agriculture is paramount, with rice serving as the primary staple for almost half of the global population and growing across all six continents, including Asia, Africa, North America, South America, Europe and Australia except the frigid continent, Antarctica [20]. In the previous year (2022/23), global rice production reached 513.68 million tons, and projections for this year estimate a potential rise to 518.14 million tons, reflecting the constant effort to meet increasing demand [18]. India, cultivating rice across 43 million hectares, faces the challenge of maintaining an average productivity of 2.6 tons per hectare [19].

The impressive yield potential of rice relies heavily on the availability of key nutrients, with nitrogen (N), phosphorus (P), and potassium (K) playing vital roles in every stage of growth. These elements serve as the lifeblood of healthy rice plants, directly impacting various life cycles, including sprouting, leafing, blooming, fruiting, and reproducing [22]. Nitrogen, a crucial nutrient, accelerates crop growth and enhances grain yield and quality. Phosphorus, another essential nutrient, serves various functions in crops, including involvement in photosynthesis, respiration, energy storage and transfer, cell division and enlargement, and internal operations. Potassium, as the third essential nutrient, is absorbed by crops in the form of K+ ions from the soil. It serves as an activator for numerous enzymes involved in various crop metabolic processes, including photosynthesis [14].

Rice cultivation, despite its significance as a global staple, faces formidable challenges due to diseases, presenting biotic hurdles that can result in yield reductions ranging from 20% to 100% [19]. Chief among these challenges is rice blast, triggered by the fungus Magnaporthe oryzae (formerly Magnaporthe grisea) standing out as the most impactful disease that inflicts annual yield losses ranging from approximately 10% to 30%. Under favourable conditions, this disease has the potential to rapidly devastate entire rice plants within 15 to 20 days, resulting in staggering losses of up to 100% [2]. The rice blast fungus, with its ability to infect and create lesions on a significant portion of the crop, progresses through various stages, commencing with leaf blast and subsequently involving collar, panicle, and node blast [16]. In the initial stages of growth, symptoms of rice blast primarily manifest on leaves referred to as leaf blast, posing a significant threat to the crop [4]. A leaf blast infection, with the potential to eliminate seedlings or plants up to the tillering stage, poses a severe threat and can lead to significant yield losses, emphasizing the critical need for effective disease management strategies in rice cultivation [5].

Routine visual assessments of rice plants stand out as one of the easiest and most efficient methods for detecting leaf blasts and nutrient deficiencies early. This process can be further enhanced with the assistance of a digital twin, offering real-time monitoring and a visual representation of the field to facilitate timely disease detection and management.

Digital twins, representing virtual counterparts of physical entities, go beyond mere representation by incorporating real-time monitoring and data integration. Through the utilization of real-time data collection, processing, and analysis, Digital Twins (DTs) provide a comprehensive digital portrayal of physical systems. This capability enables meticulous monitoring and prediction of both current and future states. It allows for the improvement of existing models and the reevaluation of systems and procedures, thus playing a pivotal role in the evolution of smart agricultural systems [15].

The characteristic feature of Digital Twins lies in the bidirectional exchange of data between tangible reality and its virtual representation. The Digital Field Twin, a key component, not only stores historical data but also serves as an interface for accessing current sensor data, including satellite images and weather data [3]. Digital twin creation is rooted in Internet of Things (IoT) devices and sensors, capturing extensive data from the physical farming environment. These sensors collect diverse data points, ranging from soil moisture levels and temperature variations to nutrient levels, crop health indicators, and machinery performance metrics. This data serves as a foundational element for agriculture digital twins, where advanced algorithms and modelling techniques analyse and interpret the information, generating a real-time reflection of the current state of the agricultural system.

In navigating the sensitive landscape of agricultural data, prioritising data security and privacy becomes paramount. Robust encryption, access controls, and strict adherence to data protection regulations effectively address these concerns. Additionally, achieving seamless integration of physical and digital systems necessitates standardised protocols, IoT integration, and middleware solutions.

At the core of this agricultural revolution is the seamless integration of digital twin technology, machine learning algorithms, and sensor data. These components synergise to offer an innovative approach to monitoring and managing nutrient deficiencies and diseases in paddy crop fields. The forthcoming sections of this paper will delve into the methodology employed in the development of the digital twin, present results and findings, and conclude with a discussion of the implications and prospects of this pioneering research.

1. Literature review

Anton Terentev et al. [21] delved into the synergy of metabolomic approaches with hyperspectral remote sensing, Raman spectroscopy, and mass spectrometry for enhanced early plant disease detection. The review navigates through proven data acquisition techniques, showcasing the potential of metabolomics in optimizing contemporary methods. The system faces challenges in achieving stability in ultra-sensitive remote sensing, particularly in hyperspectral and Raman spectrometry. The complexity and cost of advanced sensors like GC-MS and LC-MS are limiting factors.

Abbas et al. [1] explored the pivotal role of drones in plant disease assessment, emphasising the drones efficiency in monitoring and detection for smart agriculture. It utilizes LiDAR, SfM photogrammetry, multispectral, and thermal cameras to capture plant morphological information and detect diseases. The research underscores the effectiveness of deep learning models over traditional methods in disease classification. Susceptibility to environmental conditions affecting drone functionality is a key limiting factor.

Han Yih Lau et al. [11] presented DNA-based point-of-care diagnostic methods for detecting plant diseases, emphasizing characteristics like specificity, sensitivity, and multiplexing. While PCR is prevalent, isothermal techniques like LAMP and RCA offer advantages for field applications with constant temperature operation. In summary, nucleic acid-based methods offer higher specificity, with isothermal techniques presenting potential solutions, and advanced technologies like NGS requiring further refinement for practical point-of-care applications. Challenges include size variations in amplification products, and NGS, while promising, faces obstacles like complex equipment and high costs.

Bravo et al. [6] investigated the potential of spectral reflectance to differentiate between healthy and Puccinia striiformis-infected wheat plants. In-field spectral images, taken with a spectrograph at spray boom height, underwent normalization for reflectance and illumination adjustments. Leveraging a quadratic discrimination model on selected wavebands significantly reduced confusion rates from 12% to 4%. Simplifying the system while maintaining a 96% success rate, the research enhances understanding of disease detection in wheat fields. The method's reliance on ambient illumination conditions poses a potential challenge, as it may exhibit sensitivity to variations in weather and lighting situations.

Zhe Xu et al. [23] investigated the efficacy of Deep Convolutional Neural Networks (DCNNs) for the diagnosis of nutrient deficiencies through image classification in rice plants. By utilizing 1818 leaf photographs obtained from hydroponic experiments, encompassing a spectrum of nutritional conditions, the researchers fine-tuned four DCNNs: NasNet-Large, Inception-v3, DenseNet121 and ResNet50. Impressively, all DCNNs achieved accuracy levels exceeding 90%, with DenseNet121 emerging as the top performer (with a validation accuracy of 98.62% and test accuracy of 97.44%). Notably, the DCNNs outperformed traditional methods such as colour features with SVM and HOG with SVM.

Anu Jose et al. [8] delved into nutrient deficiency detection in tomato plants using neural networks. The study employed artificial neural networks to classify nutrient deficiencies in tomato plants, analysing leaf characteristics such as colour and shape. Two segmentation schemes, hue-based and threshold-based, were compared, with hue-based segmentation outperforming and achieving an 88% accuracy. The study's reliance on user identification, primarily farmers, for specific nutrient deficiency input hinders automatic detection and may introduce human errors.

Hazem M. Kalaji et al. [9] explored the utility of chlorophyll fluorescence parameters for early detection of nutrient deficiencies in rapeseed plants. Using 60 soil samples and rapeseed plants, the study employs principal component analysis, hierarchical k-means, and machine-learning methods to identify distinct groups representing different nutrient deficiency levels. The results reveal adverse effects on the photosynthetic machinery in nutrient-deficient groups, emphasizing the potential of chlorophyll fluorescence combined with machine learning for early detection. However, the research relies on soil samples from a specific geographic location and soil characteristics can vary significantly across regions, impacting the transferability of the study's findings to diverse soil compositions.

M. V. Latte et al. [10] focused on a rule-based approach to detect nutrient deficiencies utilizing HSV (Hue, Saturation, Value) colour features in paddy crops. Using HSV colour features and rigorous experimentation to establish rules, the approach achieves impressive accuracy – 100% for healthy leaves and an overall 95.39% for nitrogen, phosphorus, and potassium deficiencies. A potential drawback of the rule-based approach is its reliance on predefined rules, limiting adaptability to real-world variations. It may struggle with ambiguous symptoms and environmental factors, requiring constant rule adjustments for improved robustness and effectiveness.

Anshuman Nayak et al. [12] explored the realm of leveraging image processing and transfer learning techniques, specifically applied to the detection of rice diseases and nutrient deficiencies using smartphone images. Leveraging 2259 smartphone images, the research adeptly classified 12 rice diseases and deficiencies, pinpointing MobileNetV2 as the optimal CNN model for the 'Rice Disease Detector' Android application. Despite promising results, a notable limitation is that the user or farmer must detect the disease or deficiency, as the app focuses solely on identification and does not offer automatic detection.

Jesus David Chaux et al. [7] presented a Digital Twin Architecture designed to enhance productivity in Controlled Environment Agriculture. Utilizing simulation software, the framework enhances climate control and crop management, showcasing bidirectional communication in a greenhouse prototype. Noteworthy advantages include scalability for industrial deployment and replicability in educational settings. An additional advantage is the continuous monitoring capability enabled by the digital twin, providing real-time insights for prompt decision-making in agricultural practices. However, a potential limitation lies in the exclusive focus on controlled environments, urging future research to extend the digital twin concept to open-field agriculture.

2. Proposed methodology

The methodology employed in developing a digital twin for the paddy field focuses on guaranteeing robustness, accuracy, and user-friendly crop management tools in the designed system architecture. It begins with rigorous data handling, encompassing collection, cleaning, and augmentation. A hybrid CNN-EfficientNetB1 model is designed and trained with an Adam optimizer and key metrics for evaluation. Simultaneously, a dynamic 3D digital twin is crafted, integrating real-time sensors for effective agricultural monitoring. Fig. 1 shows the process flow of this methodology.

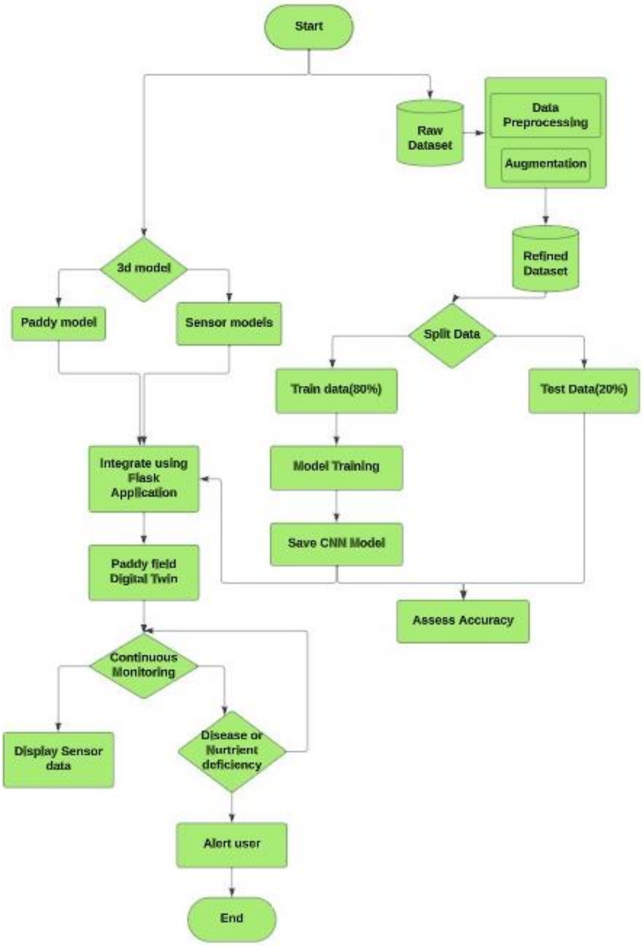

Fig. 1. Process Flow model

2.1. Data collection and preprocessing

The data collection and preprocessing procedures ensured the integrity and relevance of the dataset, comprising essential agricultural images. Two datasets were considered, both sourced from Kaggle [13, 17]. The first dataset focuses on nutrient deficiency symptoms and is organised into three folders, each representing a specific deficiency type: nitrogen (n) with 440 images, phosphorus (p) with 333 images, and potassium (k) with 383 images. The second dataset comprises 779 images depicting leaf blast disease and 1,488 images containing healthy leaves. A careful data cleaning process was carried out, involving tasks like handling missing data, duplicate removal, label consistency checks, and noise filtration. This data cleaning improved the overall quality of the dataset, providing a strong foundation for subsequent model training. The resulting dataset is categorised into distinct classes, including "Leaf Blast," "Nutrient Deficiency," and "Healthy," effectively encapsulating the diversity of conditions observed in paddy fields.

2.2. Data augmentation

Data augmentation, including random flips and rotations, was applied to diversify the dataset, improve the model's ability to generalize and mitigate the risk of overfitting.

2.3. Data loading and processing

In the data loading and processing stage, the process begins with loading the pre-trained model architecture and weights for nutrient deficiency and disease detection using the Keras library. This involves storing the model in Hierarchical Data Format (H5) and JSON files, enabling easy retrieval for subsequent predictions. An essential aspect of this stage is the implementation of an image-processing function. This function is designed to ensure that input images are appropriately resized, converted, and rescaled to meet the model's specifications. The ImageDataGenerator class from Keras facilitates the creation of data generators for both the training and validation sets. These generators play a crucial role in enhancing the model's ability to generalize by augmenting the training data with various transformations. Constants such as image size, batch size, epochs, and the number of classes are defined to maintain consistency throughout. Overall, the data loading and processing stage is fundamental for preparing the dataset, configuring the model, and establishing a robust pipeline for subsequent training and evaluation steps.

2.4. Model creation

In Model Creation, an image classification framework was built. A Convolutional Neural Network (CNN) was strategically chosen, harnessing its well-established proficiency in image classification tasks. This decision aligns with the objective of achieving robust predictions in diverse scenarios. Furthermore, to expedite the learning process and leverage prior knowledge encoded in large datasets, pre-trained models were seamlessly integrated. This integration encompassed the deployment of EfficientNetB1, recognised for its superior image classification capabilities, along with a custom-designed CNN. Incorporating these pre-trained models not only capitalizes on their domain expertise but also ensures a versatile and efficient framework capable of handling a spectrum of prediction tasks. The CNN model comprises Convolutional layers (Conv2D) for feature extraction, MaxPooling layers for downsampling and retaining essential information, and Dropout layers to prevent overfitting during training. Flattening layers convert the 2D feature maps into a 1D vector, preparing the data for Dense layers that contribute to the final classification. This combination of layers plays a crucial role in discerning intricate patterns in agricultural images, enabling the model to efficiently classify and identify nutrient deficiencies and diseases in plants.

The integration of these layers optimizes the model for image analysis tasks, enhancing its capability to recognize diverse conditions in agricultural settings. The layers in the model, encompassing both the Convolutional Neural Network (CNN) and EfficientNetB1, employ Rectified Linear Unit (ReLU) activation functions. Specifically, these functions are applied to convolutional layers, ensuring non-linearity in the model's learning. For multi-class classification, categorical cross-entropy serves as the chosen loss function, complemented by the Adam optimizer during compilation. To facilitate effective convergence, a judicious learning rate, typically set between 0.001 to 0.01, was selected. The inclusion of Batch Normalization contributes to stabilizing and expediting training by normalizing layer inputs, enhancing overall model performance. In the final compilation step, the model is configured with the specified optimiser, loss function, and metrics, laying the foundation for efficient training and robust predictions.

2.5. Model training

In the model training phase, mini-batch training is implemented with a batch size of 32 for both the training and validation sets, optimizing computational efficiency. The mini-batch sizes for both the training and validation sets are determined using a data generator, established through the 'flow_from_directory' method, an inbuilt method provided by the Keras library within the 'ImageDataGenerator' class. Throughout the training, the Adam optimizer is employed to minimize the categorical cross-entropy loss, a key factor in updating the model's weights effectively. The advancement of training is tracked by assessing accuracy as a metric, offering valuable insights into the model's proficiency in generating precise predictions. The inclusion of the 'ModelCheckpoint' callback ensures that the model weights are saved when the validation loss is at its minimum, preserving the best-performing configuration. This methodology ensures not only the efficient learning of underlying patterns but also the preservation of the optimal model state for subsequent use. The visual analysis of training and validation accuracy and loss over epochs further enhances the understanding of the model's performance dynamics. As a final step, the trained model is saved for future deployment, enabling seamless predictions of new data with the acquired knowledge.

2.6. Model evaluation

In the evaluation phase, various metrics are employed to comprehensively assess the performance of the model. The 'Accuracy' metric measures the overall correctness of the model's predictions. Precision gauges the accuracy of positive predictions, this metric is particularly relevant in scenarios where precision is of utmost importance. 'Recall', also known as sensitivity, signifies the model's ability to capture all relevant instances, providing insights into the model's ability to identify true positive cases. The 'F1 Score' acts as a harmonic mean between precision and recall, providing a balanced assessment of the model's performance. It is especially useful when there is a need to balance precision and recall in the evaluation. The 'Confusion Matrix' provides a tabular summary, offering a comprehensive breakdown of the model's performance across different classes, aiding in understanding potential areas for improvement. The 'Loss Function' value during training and validation reflects the model's learning performance, while 'Validation Accuracy' signifies the model's accuracy on the validation set during training. These metrics collectively furnish a holistic understanding of the model's effectiveness and areas for potential improvement. The specific formulas below provide insight into the quantitative measurement of different aspects of the model's predictive capabilities.

ALGORITHM 1: LEAF BLAST AND NUTRIENT DEFICIENCY DETECTION

Input: Pre-processed dataset of leaf images.
Output: Trained model for detection of Leaf Blast and Nutrient Deficiencies.
1) Import libraries: TensorFlow, Keras, NumPy, Matplotlib, scikit-learn.
2) Load and process image data using ImageDataGenerator.
3) Split data into training and validation sets.
4) Build and compile a CNN model with Adam optimiser.
5) Train the model and save it.

ALGORITHM 2: DIGITAL TWIN

Input: Crop images and sensor data.
Output: Digital Twin Display.
1) Create an html template.
2) Include hotspots for various sensors for data retrieval and implement routes to update sensor visuals.
3) Import necessary libraries and modules into the Flask app.
4) Load trained detection model from JSON and H5 files.

Implement routes to detect nutrient deficiencies and leaf blasts using the prediction function from the loaded model on crop images.

$$Accuracy \leftarrow \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \tag{1}$$

$$Precision \leftarrow \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{2}$$

$$Recall \leftarrow \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{3}$$

$$F1\ score \leftarrow 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

2.7. Digital twin

In the initial phase of the digital twin process, a comprehensive 3D model of the paddy field is crafted, capturing its layout and features. This model serves as the core component of the complete digital twin, incorporating strategically located hotspots representing sensors like pH, EC, humidity, moisture, NPK, and cameras. These sensors actively gather real-time data from the physical field, ensuring an accurate representation within the digital twin. The seamless integration of this data reflects the ever-changing conditions in the agricultural environment.

The digital twin's disease and nutrient deficiency detection capabilities are powered by an integrated model that combines Convolutional Neural Network (CNN) and EfficientNetB1. Captured images from field cameras play a pivotal role in facilitating the identification of key issues and providing timely insights for informed decision-making. Hotspot annotations in the digital twin dynamically reflect sensor status, offering at-a-glance updates on the rice crop's well-being. A user-friendly colour-coded system, with red indicating anomalies and green for normal conditions, ensures intuitive interpretation.

These hotspots, strategically positioned in the digital twin, act as informative markers, allowing users to quickly identify areas of concern and monitor specific aspects. Clicking on hotspots triggers script executions, providing detailed information about sensor readings.

Moreover, the digital twin doesn't stop at static representation; it incorporates dynamic elements like changing colours and annotations to convey the real-time nature of agricultural data. This responsiveness enhances the user experience, making the monitoring process engaging, insightful, and aligned with the dynamic nature of agriculture. The system is designed to be a user-friendly tool, enabling farmers to efficiently monitor and manage their crops.

3. Results

3.1. Training accuracy and loss graphs

The training accuracy and loss graphs provide insights into the learning progress of the combined CNN and EfficientNetB1 model over epochs. The accuracy of the model exhibits consistent improvement throughout the training process, signifying its adeptness in learning and generalizing from the provided dataset. The loss values follow a consistent trend, steadily decreasing throughout training, indicating effective convergence. Notably, the validation loss remains relatively low, affirming the model's ability to generalize well to unseen data. Fig. 2 and 3 respectively show the training accuracy and loss over epoch curves for nutrient deficiency and leaf blast detection.

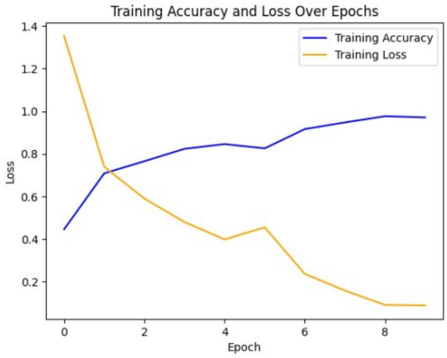

Fig. 2. Nutrient deficiency detection training accuracy and loss over epochs

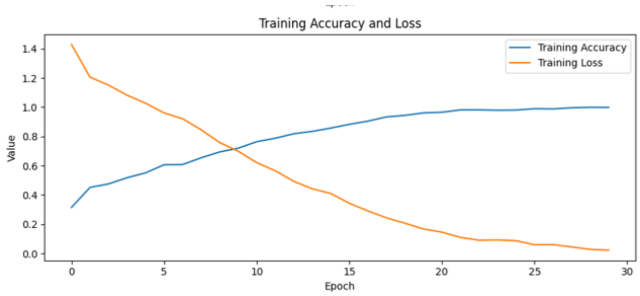

Fig. 3. Disease detection training accuracy and loss over epochs

3.2. Confusion matrix

The confusion matrix in Fig. 4, and 5 respectively illustrate the model's performance in detecting nutrient deficiencies and leaf blast in the rice crop.

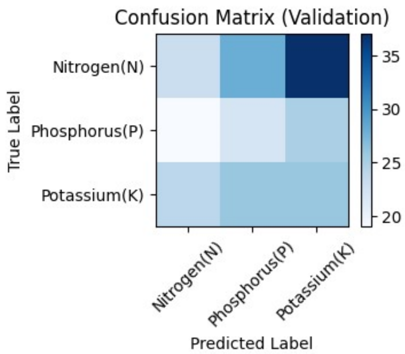

Fig. 4. Nutrient detection confusion matrix

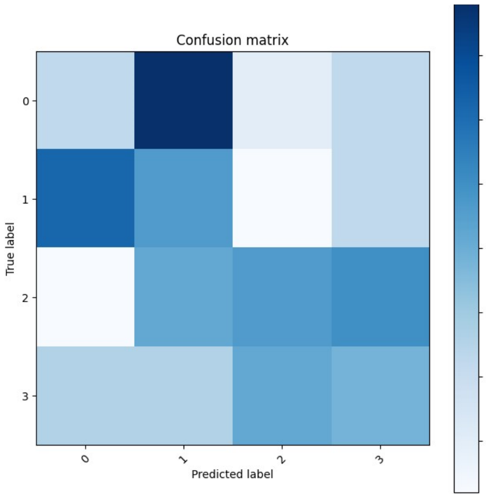

Fig. 5. Disease detection confusion matrix

3.3. Digital twin

The digital twin excelled in providing real-time insights for precision agriculture. The 3D model accurately represented the paddy field, integrating live data from strategically placed sensors. The disease and nutrient deficiency detection model, powered by CNN and EfficientNetB1, demonstrates robust performance, enabling timely decision-making in crop management. The following Fig. 6, 7 and 8 are the images of the paddy field's digital twin.

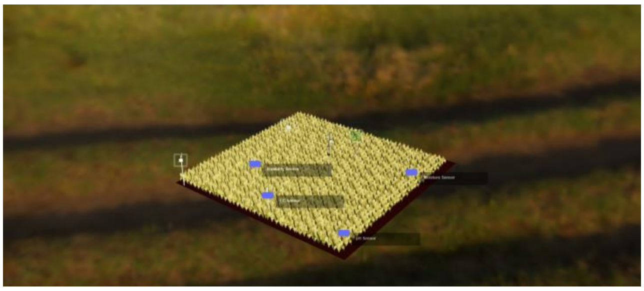

Fig. 6 . Digital Twin for Paddy Field

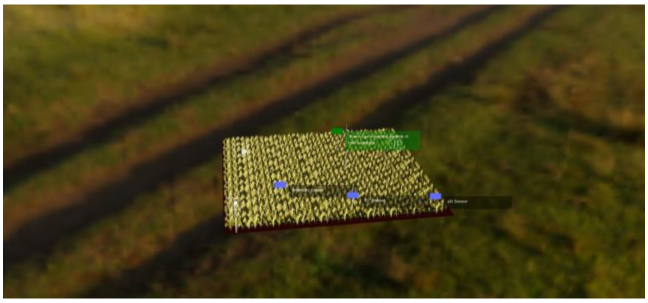

Fig. 7. Digital twin showing Healthy annotation

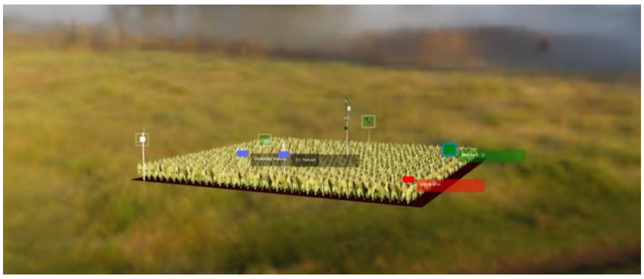

Fig. 8. Digital twin showing Imbalance of pH value

4. Conclusion

In conclusion, the digital twin of the paddy field transforms rice crop management by offering farmers the ability to monitor their fields in near real-time, providing constant insights for informed decision-making. The early detection of nutrient deficiency and leaf blast disease is a pivotal outcome, empowering farmers to address issues promptly. The machine learning model, comprising a combination of Convolutional Neural Network (CNN) and EfficientNetB1, forms the backbone of this innovative approach. Integrated into a Digital Twin framework, the model enhances the comprehensive understanding and monitoring of the agricultural landscape. This study holds the potential for expansion to encompass various crops and diseases, broadening its applicability and impact on diverse agricultural contexts. The significance of the digital twin is in its ability to enhance crop monitoring, contributing significantly to sustainable and efficient agricultural practices.

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