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MAPPING BIOTIC STRESS IN FIELD CROPS: PROSPECTS OF ARTIFICIAL INTELLIGENCE IN PAKISTAN

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A B S T R A C T

In Pakistan, agriculture and food invention classifications are facing accumulative pressures from climate change affecting biotic stresses on field crops specifically and in general on soil health and irrigation water. Pakistan has its GDP based on agriculture with major crops including Wheat, Sugarcane, Paddy and Cotton. However, data of the crops is taken manually, which is mostly labor intensive, relatively ineffective and non-scientific. Therefore, technological innovations in artificial intelligence are the most feasible and economically viable and proven options than ever to sheltered adequate food for the fast-growing population of the country. Crop maps are frequently designed using foliage indices and field data. With the recent advances in remote sensing and Artificial Intelligence (AI) such as high resolution satellite imagery analysis, deep learning and computer vision, automation and improvement in precision of crop mapping can be achieved. Now-e-days we can enumerate field scale phenotypic data accurately and assimilate the big data into analytical and prescriptive management tools. The integration of AI with geographic information systems (GIS) provides a powerful tool for real-time monitoring of accurate crop classification, plant health (Biotic Stress), crop growth, water (quality and quantity) and harvest monitoring. These models also have the capacity to do image analysis for disease diagnostics and associated management recommendations on farmers phones. It will also help to develop future training methodologies and modules according to running requirements in response to the existing biotic stresses of major field crops in Pakistan.

Keywords: Fungicides, Fusarium wilt, *Pisum sativum* L., screening, seed germination.

INTRODUCTION

The Food and Agriculture Organization (FAO) estimates that plant diseases annually cost the world economy around $220 billion and offensive insects at least 70 billion (Johnson *et al.*, 2021). Similarly, agriculture in Pakistan is faced with the relentless challenges posed by biotic stresses including pests, diseases and climate-related factors. Pakistan is highly exposed to climate change and ranked 8th on the Global Climate Risk Index that can negatively impact Pakistan agriculture (Eckstein *et al.,* 2021).

These stresses limit crop yields and ultimately the livelihoods of farmers. At the same time, technologies with the potential to provision plant disease qualification continue advancing. Considerate and envisaging variations in disease risk are vital areas for climate change adaptation of agriculture (Garrett *et al.,* 2022). Several components of systems for plant disease management can be implemented through using AI technology (Fig. 1). AI can also assimilate crucial spatio-temporal data in models of the possessions of evolving disease risk, create maps of geographic primacies for investigation and mitigation approaches and interpret these studies into applied tools for investors/stakeholders (Boch *et al.,* 2022). To explain these data and models for executives and to gather convenient data and system feedback, it will be imperative to enterprise dashboards and apps that permit operators to choose the level of detail with which they would like to involve (Fig. 2). Conversion of data for policy creators may comprise analysis of worst-case

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circumstances counting upcoming invasions in new sections and retrieval plans (Garrett *et al.,* 2022).

The emergence of new pests and pathogens threatens the very fabric of crop health. Conventional methods of stress identification and management often prove insufficient in addressing these multifaceted challenges with precision and timeliness. Most risk assessment methods necessitate particular kind of underlying disease distribution for calibration (Morris *et al.,* 2022).

MATERIALS AND METHODS:

Study Region: The study region comprised major field Crops like Wheat, Sugarcane, Paddy and Cotton in Pakistan and comparative summary table shows area, disease of the fields crop, efficiency, cost and time required in data collection by manual and AI based method is given in Table 1.

Table 1. Area, Major Biotic Stress of Crops and Efficiency of Manual and AI based Data Collection

	Wheat	Sugarcane	Paddy	Cotton
Area (Million/ha)	8.98	1.26	3.54	1.94
Major Biotic Stress	Rust	Red Rot	Blight	Whitefly
Efficiency of Manual Data Collection	70-80%			
Efficiency of AI based Data Collection	95-98%			
Cost of Manual Data Collection	High			
Cost of AI based Data Collection	Low			
Time Required in Manual Data Collection	3-4 months			
Time Required in AI based Data Collection	2 weeks			

Source: Directorate of Crop Reporting. Agriculture Dept. Govt. of Punjab 2022.

The Data can be collected in following manner: Remote Sensing Data: To initiate the process of biotic stress, a comprehensive dataset of remotely sensed imagery of field crops is required. High-resolution satellite imagery from sources such as Landsat, Sentinel and MODIS can be obtained. This imagery covers the entire spectrum of electromagnetic radiation, enabling the detection of stress indicators like changes in vegetation health and land surface temperature.

Ground Truth Data: Field data, including crop type, growth stage and health status can be collected. This ground truth data served as reference points for training and validating AI models.

Preprocessing: Image Preprocessing: The acquired satellite imagery will undergo a series of preprocessing steps. This included radiometric and geometric correction to remove atmospheric interference and rectify geometric distortions. Additionally, data fusion techniques are employed to merge multi-spectral and multi-temporal imagery.

Feature Extraction: Relevant spectral indices, such as Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) are calculated from the preprocessed imagery. These indices provide critical information about vegetation health and stress.

AI Model Development: Training Data Preparation: A portion of the ground truth data is used to train AI models. This dataset is carefully selected to represent various crop types and stress levels. Each data point is associated with corresponding remote sensing data.

Deep Learning Models: Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are employed to develop AI models. CNNs process satellite imagery while RNNs analyze temporal changes in stress indicators over multiple seasons.

Model Training: The AI models are trained using open-source deep learning frameworks like TensorFlow and PyTorch. Training involved optimizing model parameters to minimize prediction errors and enhance accuracy.

Biotic Stress Mapping:

Stress Detection: The trained AI models are applied to the entire dataset of remotely sensed imagery. They analyzed the spectral indices and other relevant features to detect and classify biotic stresses in field crops.

Validations: Cross-Validation: To ensure the accuracy and robustness of the AI models, cross-validation techniques are employed. The remaining ground truth data, which was not used for training is utilized to validate model predictions.

Accuracy Assessment: Various metrics, including precision, recall, F1-score and overall accuracy is computed to assess the performance of the AI models in stress mapping.

Result Visualization: Spatial Mapping: The detected stress areas are visualized using Geographic Information Systems (GIS) tools. These maps are provided with spatial representations of stress distribution in field crops across Pakistan.

Model Optimization and Scaling: Scalability: The AI models are then optimized for scalability, enabling them to process large volumes of satellite imagery in real-time or near-real-time for continuous monitoring.

Data Integration and Decision Support: Data Integration: The stress mapping results are integrated with relevant weather data, historical crop yield data and other environmental factors.

Decision Support System: An AI-driven decision support system is developed to provide actionable insights to farmers and policymakers. It included recommendations for crop management practices and resource allocation to mitigate the identified stresses.

DISCUSSION

This study employed a systematic approach encompassing data collection, preprocessing, AI model development, validation and result visualization to prospect the application of Artificial Intelligence in mapping biotic stresses in field crops across Pakistan. Previously, such tools have helped farmers improve 40-50% in water use efficiency, 20-30% in input efficiency, 20-30% in yield increase and 30-40% improvement in waste management (FARMDAR, 2022). This methodological framework offers a powerful tool for enhancing agricultural resilience and productivity in the face of evolving biotic stresses.

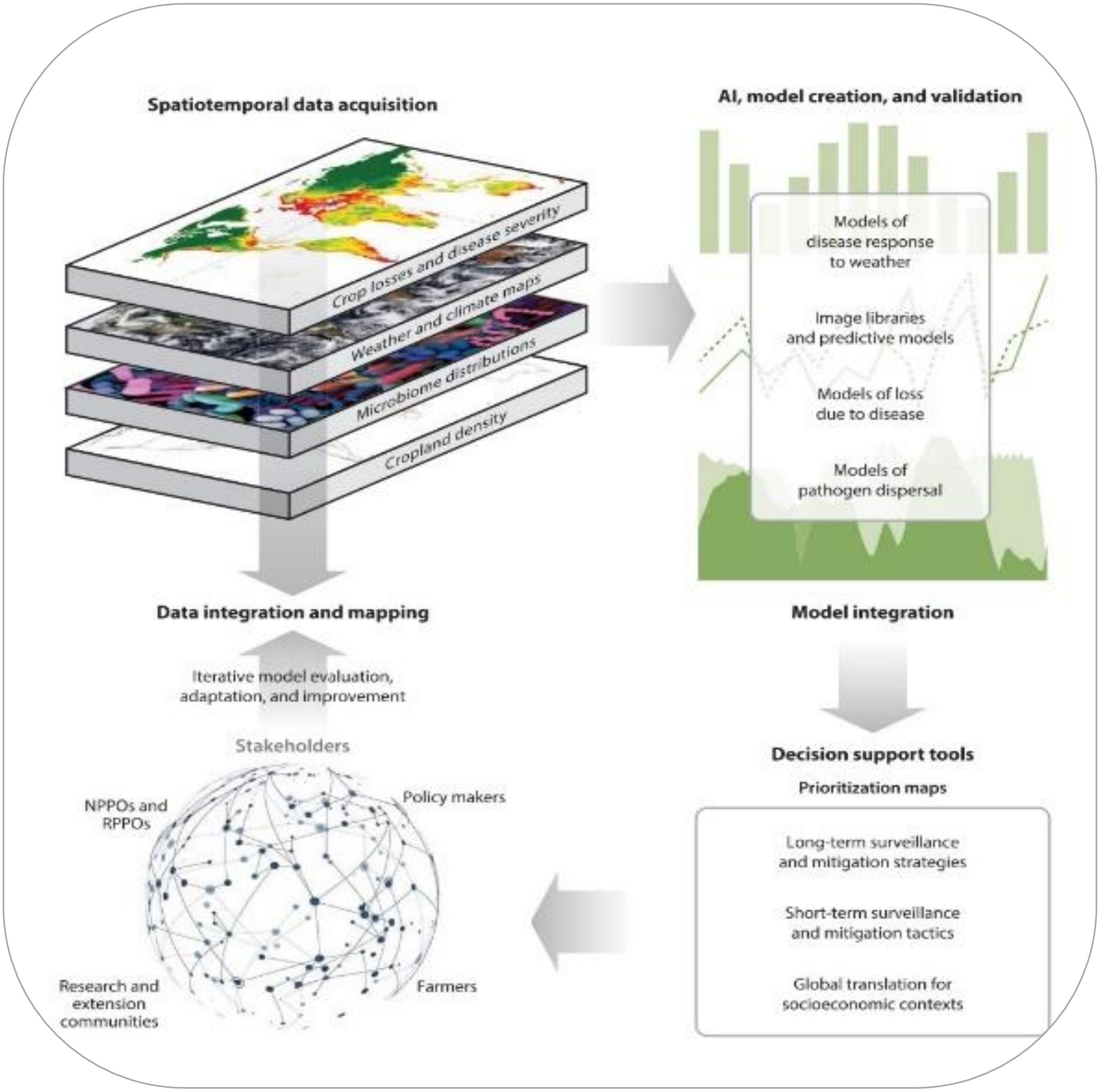

Figure 1. Artificial Intelligence Data Management

Figure 2. Pest & Disease Detection Application

CONCLUSION

Artificial intelligence can certainly improve model schemes accordingly that they are organized for both predictable and unpredictable biotic stresses in Pakistan. These models and tools have modernized reconnaissance and mitigation programs against plant diseases and would help in planning before time. The model discussed in (Fig. 1) is helpful in finding (a) disease incidence and rigorousness (b) plant host density and resistance gene deployment (c) experimental and predicted future climate variables and fine-resolution weather variables, (d) Digitalized data (e) trade linkages and (f) running practices and their efficiency.

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Contribution of Authors:

Minahil Shahzad: : Planning, evaluation, Write up and Data Collection of the paper