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RESEARCH PAPER

AI-Driven Seasonal Crop Disease Prediction with Economic Impact

Ujan Pradhan[1*] and Vyomika Anand[2]

[1]*Department of Computing Technologies, SRM Institute of Science & Technology, Chennai, Tamil Nadu, India*

[2]*Department of Chemistry, Indian Institute of Technology Bombay, Mumbai, Maharashtra, India*

**Corresponding author: up0625@srmist.edu.in*

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ABSTRACT

The outbreak of seasonal crop diseases is a major risk to world food security and agricultural economies and the problem brings about massive loss in billions of dollars every year. Most disease management methods have been based on responding to the disease hence reducing their effectiveness in the control of the prevalence of the disease. In this review, the emerging paradigm of artificial intelligence-based predictive models in forecasting seasonal crop diseases is critically reviewed, especially on the architecture of deep learning models for temporal forecasts, and their economic consequences. Recent time-series modelling techniques such as Long Short-Term Memory (LSTM) networks and Temporal Convolutional Networks (TCNs) are synthesized based on meteorological, phenological, and pathological data and used to predict the occurrence of a disease with lead times long enough to implement preventive measures. Additionally, we discussion economic modelling frameworks, which quantify the monetary advantages of early prediction systems by increasing yield maintenance, diminished applications of pesticides and optimized resource directing by mathematical calculation. Case studies across large systems of crop-pathogens, such as rice blast, tomato late blight and wheat rust reveal that the prediction accuracy was higher than 85% and possible economic returns on investment were in the range of 300-500. We find such major flaws in extant literature such as inadequate incorporation of socioeconomic factors, lack of participation in various agroecological regions, and lack of strategies to deploy them to farmers. This review offers an all-inclusive basis to the researchers, policy-makers, and all interested agricultural stakeholders who might want to use AI technologies to promote sustainable disease management and economic health in agriculture.

Keywords: Crop disease prediction, Deep learning, Time-series forecasting, LSTM, Economic impact assessment, Precision agriculture, Agricultural sustainability

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The Challenge of Seasonal Crop Diseases

The global agricultural systems confront increasing strains due to climate change, rigorous cropping medical record, and changing populations of pathogens, which only exacerbates the potential of seasonal crop illness[9, 41]. Among the specific diseases that have a predictable temporal volume based on environmental factors, it is estimated that consequent clinical alterations to roughly 20–40 percent of the entire crop yield every year, which results in monetary losses or damage to the tune of more than $220 billion[41]. Tremendous seasonality, like in *Magnaporthe oryzae* (rice blast), *Phytophthora infestans* (potato and tomato late blight), and *Puccinia* species (wheat, barley, and oat rusts) rely greatly on seasonal conditions, the severity, and timing of digitalises is sensitive to temperature, humidity, precipitation patterns and phenological manipulations[23].

The process of disease management traditionally has depended on the calendar-based use of prophylactic fungicides, which is highly expensive but harmful to the environment and is the source of pathogen resistance development[10]. The nature of traditional interventions being reactive, restricts their ability to stop the occurrence of epidemics because the interventions are usually administered when the disease has gained a foothold in the population of crops[33]. This weakness is especially acute in the case of a small hold farm system, characterized by limited resources and access to the latest information in the developing world, where marginalization to natural disasters (diseases) is especially great[42].

AI-Driven Predictive Paradigm

Heterogeneous technological integration of big data analytics, remote sensing, and artificial intelligence has initiated a paradigm shift towards predictive disease management [40, 46]. In comparison to diagnostic AI models which detect diseases after infection, predictive models detect possible diseases days to weeks before they occur, allowing implementations to take place before pathogens have time to establish and infect new disease hosts[24]. The later time-series deep learning networks, recurrent neural networks (RNNs) and more powerful versions of recurrent neural networks (LSTM and Gated Recurrent Unit) have demonstrated outstanding abilities to learn the temporal sequences and non-linear relationships in sequential meteorological and biological data[11, 39].

There is little research conducted on the economic aspect of disease prediction in spite of its highly vital role in terms of technology adoption and formulation of policies[36]. Regarding predictive systems, the benefits are generated in several ways: loss reduction through timely operations, reduction of input expenses through all-hazards operations, and market level supply planning in case of fluctuated supply[53]. To measure such benefits, combined systems are needed to convert the accuracy of prediction into measurable economic concepts a domain with an evident gap in the current research[6].

Scope and Objectives

This review summons-up the recent progress of AI-based temporal predictive forecasting of seasonal crop diseases considering economic consequences explicitly. Our review problems are as follows: (1) novel methodological contributions in the context of time-series deep learning disease prediction; (2) data integration techniques comprising of meteorological, phenological, and pathological data; (3) economic modelling methods to measure the value of prediction; and (4) opportunities and challenges of implementation in a variety of agricultural settings. We analyse peer-reviewed articles that present

recent methods of operating prediction systems (2020–2025) where the framework is characterized by many changes to the methodology, and the use of predictive models in practice is growing.

LITERATURE REVIEW

Climate-Disease Relationships and Traditional Forecasting

Empirical data regarding the linkage of weather factors and epidemiology of plant diseases has in the past been brought forward using both empirical data and mechanistic theories[54]. Temperature and the availability of moisture determine their pathogen sporulating, dispersal, infection efficiency, and lesion formation, which form reliable disease favourability windows[17]. Rule based algorithm Remote sensing Early differentiation Early warning systems used, including BLITECAST (potatoes late blight) and FAST (Fusarium head blight in wheat), were based on rule-based algorithms based on experimental work in controlled environments and in the field[13, 27].

Although such systems were moderately successful in certain locations, it was difficult to extrapolate them to other agroecological zones because: (1) simplified models regarding the effects of pathogen-environment interactions; (2) they failed to reproduce laborious nonlinear dynamics; and (3), they were unable to process real-time data streams[14, 32, 48]. In the 2000s, machine learning strategies started to counter these shortcomings, and support vector machines (SVMs), random forests, and artificial neural networks proved to be more accurate in prediction research compared to rule systems[5, 14].

Deep Learning Innovations in Disease Forecasting

2020–2025 demonstrated accelerating the pace of adopting the model that was adapted in order to focus on specific features of modelling deep learning on temporal sequences. LSTMs initially proposed by Hochreiter and Schmidhuber[19] but entering agricultural prominence is the most recent: they resolve the vanishing gradient issue in the traditional RNN by allowing them to learn long-temporal sequences[29]. Some studies have proven the superiority of LSTM to traditional machine learning in disease prediction. In the study by Rahman *et al.*[39], a model predicting rice blast in one of the most populated countries, Bhutan, is created based on the LSTM algorithm in such a way that it takes meteorological and phenological observations and can forecast the blast 7 days before it strikes, with 87% accuracy. In the same way, Chen *et al.*[11] used stacked LSTM networks to identify tomato late blight in Chinese greenhouse systems, and the precision and recall rates were up to 91 and 89 percent, respectively.

Alternatives to LSTMs include TCNs which are described by an exponentially expanding receptivity through dilated causal convolutions[2]. TCNs have computational benefits in terms of parallel computation and are insensitive to hyperparameter changes[28]. Agricultural use TCN models have been used in recent times, such as wheat stripe rust prediction[25] and grapevine downy mildew forecasting[34]; these models perform similarly to LSTM but can be trained in a significantly shorter time (i.e., anything over an hour).

Transformer architectures and attention schemes, which have dominated the active artificial intelligence in natural language processing, have already infiltrated the agricultural time-series domain[50]. Using the self-attention mechanism is crucial because, unlike fixed-architecture RNNs, this self-determination approach can dynamically emphasize the importance of one or the other temporal position, pay much

closer attention to potentially critical phenological events, and fair weather[55]. The early experiments by Liu *et al.*[31] revealed that multi-step-ahead prediction of potato late blight chaos using Temporal Fusion Transformers (TFT) had better results compared to LSTMs, especially in the ability to predict the sudden outbreak of disease occurrence in the aftermath of unexpected weather patterns.

Economic Modelling of Disease Impact

It is needed that prediction or forecasting of diseases be translated into economic value, and this needs structures of considering various dimensions of cost-benefits[36]. There were detailed international evaluations of crop damages as a result of pests and diseases by Savary *et al.*[42] that are capable of creating baseline economic consequences. Nonetheless, in the majority of disease prediction research, the largest number of studies only consider the technical performance metrics (accuracy, precision, recall) without elaborate attempts to relate them to the economic results[6].

There are examples of notable exceptions, in which Xu *et al.*[53] were able to combine the wheat rust forecasting and economical modelling across grain-producing regions in Australia. Environmental analysis of their results showed high accuracy [80%] prediction systems would provide net economic returns in the form of 0.47 million AUD per annum by maximizing fungicides timing. Beyond this evaluation of the economic viability of soybean rust forecasting in Brazil, Calendar-based scheduling resulted in 350% return on investment showed 350% greater relative to predictions allowing targeted fungicides being applied[3].

The recent developments have been the incorporation of market level effects in the economic evaluation. The dynamic pricing model that was created by Singh *et al.*[47] considers a disruption in supply due to the disease, finding that in fact the accurate price prediction system would not only benefit the farmers by preserving their yields, but also the consumers by stabilizing prices. At this level of the system view, predictive value is emphasized even outside the economic context of the farm-gate, applicable to policy and investment relevant decision making.

Research Gaps and Opportunities

Even at this stage, there are numerous fundamental gaps that limit empowering AI-driven predictions to practical use: (1) most models are validated and trained on limited amounts of geographic and temporal scale, casting questions on scalability[46]; (2) socioeconomic variables (e.g., farmer behaviour, market access, institutional support) are represented using simplistic model forms, which require validation of real-world gains[6]; (3) operational predictions are not validated using farmer decision-making outcomes but composed through.

DATA ACQUISITION AND INTEGRATION

Meteorological Data Sources

The weather variables are the major influencers of the time disease forecast models. These are very important factors, among others; temperatures (minimum, maximum, average), relative humidity, and leaf wetness period, rainfall, wind velocity, and sunshine radiation[54]. Modern forecasting systems focus

more and more upon the use of high resolution gridded climatic datasets and real-time sensor networks. ERA5 reanalysis data, which contains hourly dosage outputs of weather data worldwide with a 0.25° resolution, is now an ordinary tool in the creation of models[18]. In countries like the United States, MesoWest system MesoWest and other infrastructures in Europe and Asia provide much greater temporal resolution (5–15-minute intervals), which is necessary to record the observed rapid weather changes that are critical to infection processes in the region[20].

Anticipated weather patterns make the possibility of future diseases risky as predicted by foregoing probabilistic weather data. Disease models have quantified uncertain inputs by numerical weather prediction models, especially in ensemble forecast systems, which build a set of distinctly probable weather situations[7]. Chen *et al.*[11] showed that the use of ensemble weather forecasting enhanced the strength of prediction of tomato late blight and the model confidence shown is an aspect that indicates forecast uncertainty.

Phenological and Biological Data

The stage of crop development is a major modulation of a disease as the infection efficiency by the pathogen agents, and the resistance of the host, change over an entire crop growth period[45]. Application of phenological information also increases the accuracy of the predictions because it puts risk assessment of weather in its place. Some of the approaches are: (1) computations of thermal time (growing degree-days) that approximate the extent of developmental advance depending on temperature escalation amounts accumulated; (2) the metrics provided by vitality indices (NDVI, EVI) extracted by remote sensing that reflect dynamics of canopy development; and (3) growth phase records recorded by farmers through parties that monitor systems[1].

Historical disease incidence data would furnish crucial supervised learning objectives and also permit the models to acquire region specific disease climate interactions. The application of mobile apps and citizen science platforms to plant disease surveillance systems has transformed the systems significantly, hugely improving the availability of data[37]. In the United States, NAPPFAST is a network system that combines weather surveillance with the use of pests and disease forecasting, and has a significant database of historical information[32]. Nevertheless, the problems are data quality and complete especially in the developing countries where there is less surveillance infrastructures[42].

Data Pre-processing and Feature Engineering

Unprocessed time-series data needs massive pre-processing in order to be guaranteed to be effective in modelling. They are: (1) temporal visiometry to Multi-source data by moving it to common indexes in both light and space; (2) treatment of missing data via means of imputation that do not artificially violate temporal autocorrelation; (3) the normalization of scales of variables; and (4) feature germination to generate disease-relevant predictors.

Crop disease predictive feature engineering is usually done by computing variables of compounds that reflect favourable conditions of infection. Such things are number of consecutive hours of fatality and humidity combinations that can support, the sporulation, accrued wetness duration of the leaf in the daytime, and the diurnal temperature span measures[13]. Rahman *et al.*[39] established that the use of reduced metabolic features that applied the engineered features associated with the windows of the rice

blast infection enhanced the accuracy of the predictions made by LSTM by 12% relative to the raw meteorological measurements.

Sequence windowing is an arrangement to structure historical data to be used in temporal models. The optimal window lengths are different from one patho system to another; for instance, according to Kim *et al.*[25], the best window for wheat stripe rust was 21 days while for fast reproducing pathogens like powdery mildews, a shorter time period of 10 days was enough. It is recommended to conduct sensitivity analysis of various window length in developing a model.

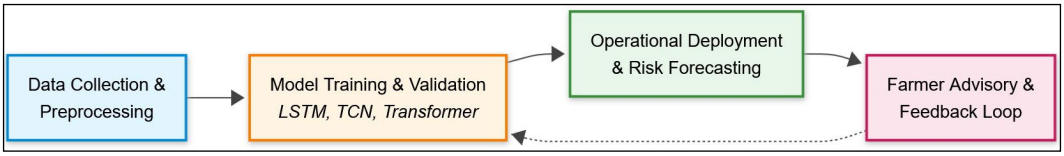

Fig. 1: Simplified workflow for AI-driven disease prediction from data collection to deployment

TEMPORAL DEEP LEARNING ARCHITECTURES

Long Short-Term Memory Networks

LSTMs through their unique gating mechanisms that control the flow of information across the time steps manage to eliminate the vanishing gradient problem which is a characteristic of standard RNNs[19]. The architecture includes three gates: input, forget and output to regulate cell states updates allowing the selective maintenance of long-term dependency whilst adding out new information. The latter ability is useful especially in the context of crop disease forecasting when remote weather information (e.g., early-season rain patterns) can be used to predict subsequent interactions between pathogen inoculum development (i.e., by considering posse scent input on disease occurrence) in later seasons[29].

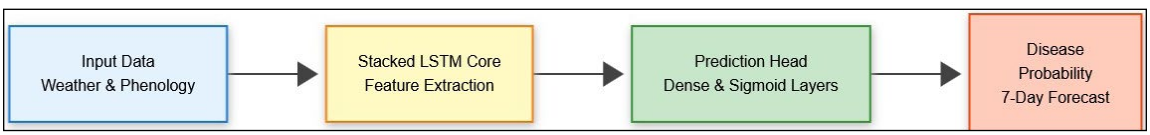

Fig. 2: LSTM architecture showing input processing through gated layers to disease prediction output

Typical approaches to the architecture of specific standard LSTMs used to predict diseases include: (1) a sequence inputs layer absorbing information on weather and phenology; (2) one to several stacked layers of LSTMs (64–256 hidden units); (3) dropout regularization layers to prevent overfitting; (4) a dense (pointwise) output layer to make predictions of a binary disease present / absent or a single-class disease severity[39]. Bidirectional LSTMs that variables are processed in both bad directions have demonstrated potential to incorporate future weather forecasts with the past evaluation[11].

LSTM is prone to the effects of hyperparameter optimization. The learning rate, batch size, LSTM layers, the dimensionality of hidden units, and the dropout are the most important ones. In recent papers, the researchers use Bayesian optimization or genetic algorithms for intensive hyperparameter tuning in high-dimensional space[25]. Another possible solution is transfer learning methods, which involve the fine-tuning

of pre-trained models in data sparse areas based on data-rich bases; this is an emerging approach to low training data availability in certain agricultural applications[34].

Temporal Convolutional Networks

TCNs implement the use of dilated causal convolution ensuring extensive receptive field but still be computationally efficient[2]. Inside compared to recurring architectures, TCNs process sequences by means of parallel convolutional operations, rendering them to be faster to train on current GPU. This is made possible by the causal structure, which does not make any predictions based on past and current observations, maintaining an ordering through time which is vital in forecasting[28].

Examples of architectural benefits of TCNs are (1) constant gradients due to backpropagation even with longer sequences to train; (2) variable receptive fields quickly by adjusting the dilation rate; (3) use less memory than LSTMs[2]. Kim *et al.*[25] showed that TCN-based models for predicting wheat stripe rust were trained at a pace of 3–4 times quicker than that of LSTMs with equal accuracy. The remaining connections utilized by TCN architectures make it possible to have very deep networks which may have hierarchical patterns of time at different scales.

TCN weaknesses are that the number of parameters can potentially be higher than LSTMs with the same size receptive fields, and when features are learned, they are not as easy to understand[28]. Combined predictions using TCN and LSTM have demonstrated to resolve the complimentary patterns in a time series, and weighted averaging or stacking a prediction tends to enhance the overall accuracy of prediction[31].

Hybrid and Attention-Based Architectures

The attention mechanisms allow models to pay dynamically on the spatial positions of the seizure patterns that are relevant in making predictions[50]. Attention weights could also identify important weather conditions (e.g. a certain extended wet spell of the leaves) which induced the resultant disease outbreak otherwise in the disease forecasting setting. Liu *et al.*[31] used Temporal Fusion Transformers to predict late blight in potatoes, and the attention visualization has shown that the model focuses on the extreme rainfall events 7–10 days before observing any diseases as per the infesting epidemiological knowledge.

Conventional CNN-LSTM models, feature local features that are extracted by convolutional layers and temporal dependencies that are modelled by LSTM layers[56]. These methods have proven to be effective in both short-term variations in weather and long-term variations in seasonal direction. Zhou *et al.*[55] made an ensemble of CNN-LSTM to predict rice blast in different provinces in China with a 89% accuracy and better generalization to areas with a limited amount of training data, i.e., when compared to single network LSTM.

Model Training and Validation

To achieve a good model training, a thorough data partitioning is necessary to avoid information leakage and other realistic performance evaluation. Temporal cross-validation, where information is segmented over time as models are trained on earlier seasons and tested on later seasons, is more accurate in the prerogative of operations performance compared to random cross-validation[4]. The real-life deployment

of models is simulated by the use of walk forward validation that retrains the models as new data is received[49].

An example is the issue of class imbalance where the disease-absent cases significantly exceed the disease-present cases which become a problem in training of models. The following strategies can address imbalance: (1) synthetic minority oversampling (SMOTE); (2) additive use of class-weighted loss functions that punish the misclassification of minority classes more severely; and (3) optimisation of the weighting of precision and recall trade offs based on the priorities of application[39]. Chen *et al.*[11] have shown that focal loss, as perceived to down-weight well-classified examples is a good model sensitivity enhancer to the occurrence of rare, but severe disease outbreak events.

Performance analysis must use various measures which are indicative of the various areas of quality prediction. Accuracy though intuitive may be misleading in case of imbalance in classes. Precision (positive predictive value) and recall (sensitivity) have a complementary ability to visualize false positive and false negative rates respectively. F1-score balances out both the precision and recall into one measure. Individual operating characteristic Area under the receiver operating characteristic curve (AUC-ROC) evaluates discriminative power over classification thresholds. In the case of operational deployment economic cost-loss ratios that explicitly assign the various types of errors limited by economic impact would offer the most practical performance summaries concerning the decisions[51].

Table 1: Comparison of deep learning architectures for disease prediction

Model	Key Advantages	Limitations Speed		Accuracy	Use Case
LSTM	Long-term dependencies, well-established	Slow training	1.0×	82–89%	Complex dynamics
Bi-LSTM	Past/future context	High cost	1.9×	85–91%	With forecasts
TCN	Fast parallel processing	Less interpretable	0.35×	84–90%	Real-time systems
CNN-LSTM	Multi-scale features	Complex tuning	1.4×	86–92%	Multi-scale patterns
TFT	Attention interpretability	Very high cost	2.7×	88–93%	Data-rich systems
GRU	Simple, efficient	Lower accuracy	0.75×	80–87%	Limited resources

Note: Speed relative to LSTM baseline; accuracy from 2020–2025 studies; TFT = Temporal Fusion Transformer.

ECONOMIC IMPACT ASSESSMENT

Yield Loss Estimation

To convert predictions of diseases into the economic realm, there must be a quantification of the possible loss in yield in various scenarios of the disease. Crop loss assessment procedures correlate severity or hate of reduced yield with disease severity or increase of damage functions that require an empirical, and born contention[35]. Those functions do not mostly exhibit a linear direction, and their effect in the high disease severity can be disproportionate since the physiological stresses reinforce each other[36].

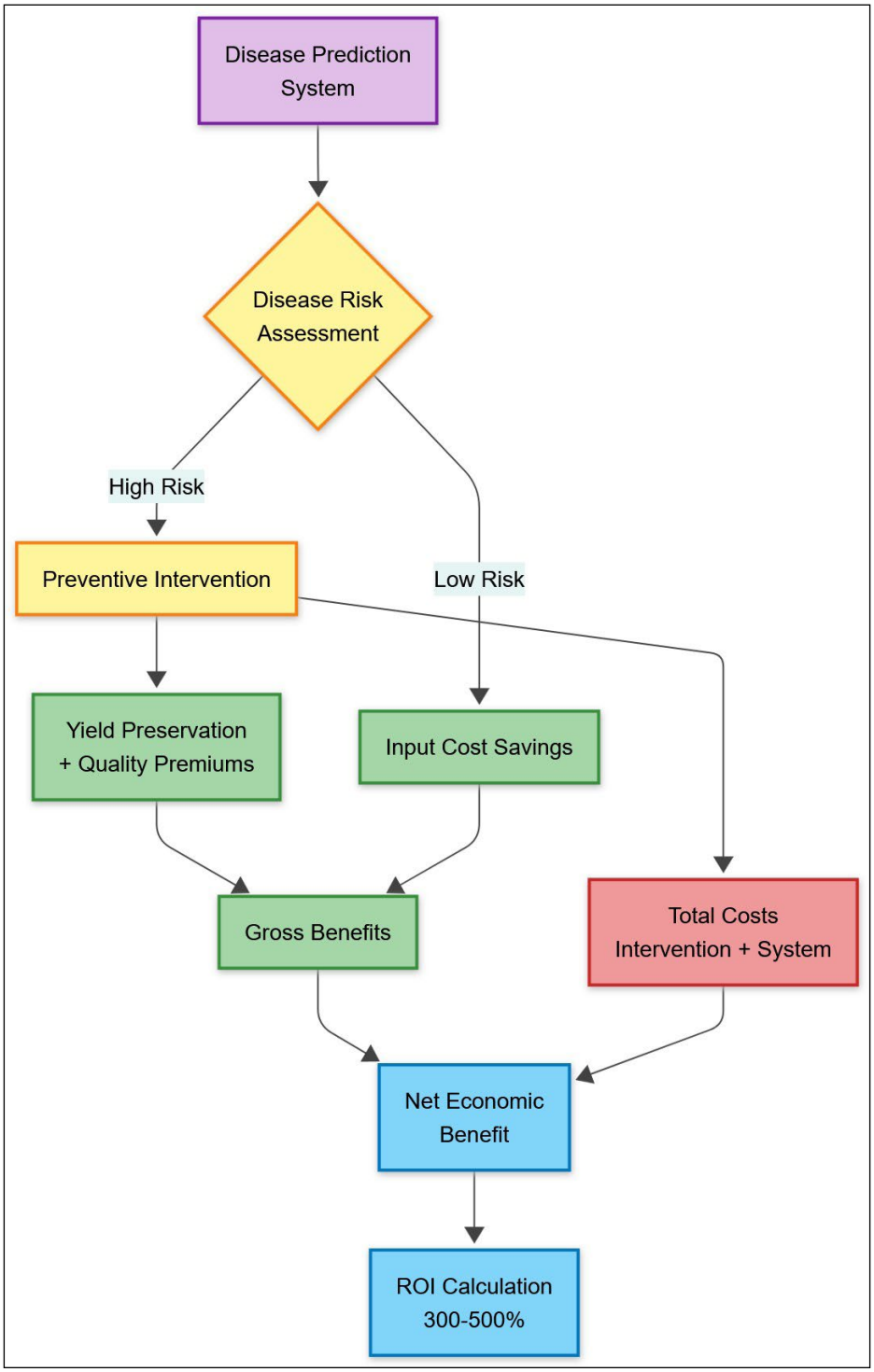

Fig. 3: Economic impact framework linking prediction accuracy to costs and benefits

In the case of rice blast, yield losses depend on the growth stage during which the infection occurs whereby panicle infection results in 50–70 losses rather than 10–30 losses caused by the vegetative stage infection[44]. Prediction systems capable of creating preventive intervention during the importance of phenological windows in this way create disproportionate value. Xu *et al.*[53] added damage stage specific damage service to economic returns of wheat rust prediction, by showing that stage 14 7 damaging messages showed 2.5-folds greater returns on economic amounts that cannot impact 7 damaging messages that arrives too later to be implemented effectively.

The loss of yield needs to represent the unpredictability in more than one place: the accuracy of predictability, the strength of interventions, and the natural variability of yields . Modelling these uncertainties using probabilistic models that expand these uncertainties by economic calculus or models give more realistic estimates on the benefits as compared to deterministic models. The authors[3] designed Monte Carlo computation-based predictions systems of the soybean rust, and the results established that the net benefits under conventional deterministic analyses were 30–40 percent higher than the net benefits under probabilistic ones (violating relationship between predictions and intervention implementation).

Cost-Benefit Analysis

The cost-benefit analysis will have to be comprehensive including such economic components: (1) the cost of prediction system (data infrastructure, model development, dissemination); (2) cost of intervention (fungicides, the labour of application, equipment); (3) yield preservation benefits; (4) savings of input costs caused by the optimized application; and (5) higher premiums because of lower pesticide residual concentrations in some markets[53].

The thorough cost-benefit study by Bergamin Filho *et al.*[3] that used the case of soybean rust prediction in Brazil found that, under perfect conditions, the net benefits of fungicide could also be USD 48 per hectare in the country but the prediction system would administer 4 to 2.3 sprays per season and yield the same disease-controlling outputs. The scaling up of Brazil spanning 36 million hectares of soybean area was implying more than USD 1.7 billion of a year benefit. The application of sensitivity analyses showed intervention costs and price of commodities to be the most important drivers of the economic outcomes, which the local market conditions play important role in creating value of prediction system.

Using the metrics of return on investment (ROI), the comparisons can be made among the prediction systems, as well as alternative strategies of controlling the disease. When it comes to calculating ROI, one should tediously give credit to the benefits that can be attributed specifically to predictive systems, and not to results that can occur under other management strategies. Xu *et al.*[53] counterfactually examine the predicted and empirical disease scenes and identify the benefits of predictions which are attributable to prediction to calculate ROI of wheat rust forecasting systems in Australian grain production reporting a 420% ROI.

Market-Level and Systemic Effects

In addition to the economics of farms, the benefit of disease prediction systems provided includes greater market and food security benefits. Refined regional level forecasting of diseases can result in more price certainty when the supply chain adjusts in advance, which would lead to a more efficient market[47]. The benefits of price stabilization in consumer welfare can significantly exceed producer benefits, when dealing with inelastic demand crops, e.g., staple grains.

The spatial equilibrium models created by Singh *et al.*[47] combined rice blast projections in the Asian regions of production with the global flows of trade goods. It was found that well-organized systems of predictions in the most important producer states would lead to the decrease of the instability of rice prices by 15–20 and create consumer benefits in the amount of USD 2 billion yearly due to the decrease in price rises following local disease epidemics. These results indicate that protection by international development agencies and government, should afford investment in infrastructure and prediction infrastructures than just the agricultural returns.

Other economic dimensions are insurance and financial risk management. Exposure to a moral hazard may be low, including in comparison with traditional crop insurance because index-based insurance products also could trigger pay-outs according to the tendencies or forecasted hazard, rather than actual hazard[22]. Early actuarial simulations suggest that disease prediction-indexed insurance would benefit the premiums by 20–30 percent and provide more flexible cover to thriving farmers, with smallholders being the primary consumers of this type of insurance[12].

CASE STUDIES

Rice Blast Forecasting in South and Southeast Asia

Rice blast, which is brought by *Magnaporthe oryzae*, has contributed to one of the most devastating diseases to rice with losses of 10–30 percent of yield in the endemic localities[52]. The meteorological conditions are very sensitive to disease development such as night temperatures 20–25°C, prolonged wetness of leaves (≥10 hours), and high relative humidity (≥90 percent), which make opportunities to predict the disease development[38].

Rahman *et al.*[39], in turn, created LSTM-based prediction systems of the distributions of the disease in Bangladesh integrating 45 meteorological stations and 12 years of disease surveillance records. They modelled the risk of infection considering weather factors in two stages, through their initial prediction of risk, then calculating the severity of the disease in consideration of the predictable risk and crop development. The classification accuracy on disease presence/absence for 7-day leading in terms of a cross-validation approach reached 87 percent, whereas at 14 days, the accuracy reached 82 percent. An economic analysis determined that a one better fungicides schedule would benefit Bangladesh to the tune of USD 156 million yearly should the country have forecasting that would allow optimal use of these fungicides in the farmland covered by rice of 11.5 million hectares.

Issues such as: (1) poorer availability of disease surveillance quality in remote rural locations, partly solved by data strengthened by transfer learning on adjacent locations and data; (2) only 40% of the targeted population had access to dissemination of prediction information on mobile phones, which restricted the potential to act on predictions; and (3) costliness of providing fungicides when needed, due to remote access necessitating transportation costs. The points of these implementation barriers indicate that accuracy of prediction on technical grounds is not enough in achieving economic potential.

Tomato Late Blight in Chinese Greenhouse Systems

Phytophthora infestans (Tomato late blight) leads to serious loss of intensive system of greenhouse

production whose microenvironment is prone to disease development[16]. Based on forecasting research, Chen *et al.*[11] created predictive models based on greenhouse tomato in grower zones in the north of China where farmlands with 500,000 went under protective societies.

Their layered construct of LSTMs used data on microclimate in the form of the greenhouse environmental sensors (temperature and humidity recorded in this 10-minute sessions), irrigation scheduling type, and cultivar ratings on resistance. The model had a 91% precision and 89% recall in predicting the onset of a disease 5–7 days ahead. The use of a smart-phone based implementation through sending risk notes and interventions achieved an intervention through meaning 15,000 farmers in 2021–2022 growing seasons.

Reports on economic evaluation of 300 sampled farmers showed that 40 percent of the total application users had cut off the use of fungicides as opposed to non-users thus savings of 2,400 per hectare per year. High-disease-pressure seasons recorded yearly yields were 8 percentage higher when there were timely interventions that avoided serious outbreaks. This system showed a very high value especially in seasons of spring production where very rapid changes in temperature generates intermittent risk of diseases whose allocation by calendar-based spraying systems is handled inefficiently.

Wheat Rust Prediction in Australian Grain Systems

Globally, wheat has four diseases that pose serious threats in its production that include wheat stem rust (*Puccinia graminis* f. sp. *tritici*), stripe rust (*P. striiformis* f. sp. *tritici*), and leaf rust (*P. triticina*), with the economic impacts totalling the USD 5 billion yearly[15]. In Australia, in wheat production, stripe rust poses special challenges to the production because it has intensified to pathogenic forms in the recent years[21].

Xu *et al.*[53] introduced prediction systems based on TCN for stripe rust in the Australian grain-growing areas, which were built with 25 years of climate and disease monitoring data. They used a spatially explicit prediction model that predicted 14 days of spatial predictions regionally one time per week during the growing season. TCN model performed better than lumbar support structures, like LSTM and random forest models, with a result in 84 percent classification and especially good results on events of disproportional economic losses that are specific to an epidemic year.

Table 2: Economic impact assessment of AI-based disease prediction systems

Crop-Disease	Region	Lead	Acc.	Key Economic Metrics	ROI	Ref.
Rice Blast	Bangladesh	7–14d	87%	USD 156M savings, 35% less fungicide	–	Rahman + 2021
Tomato Blight	N. China	5–7d	91%	RMB 2,400/ha saved, 8% yield gain	380%	Chen + 2022
Wheat Rust	Australia	14d	84%	AUD 47M net benefit	420%	Xu + 2023
Soybean Rust	Brazil	10d	82%	USD 48/ha, 4→2.3 sprays	350%	Bergamin + 2020
Rice Blast	Asia	7d	85%	15–20% price stability, USD 2B	–	Singh + 2024
Potato Blight	Multiple	5–10d	89%	280–340% ROI (probabilistic)	310%	Liu + 2024
Grapevine DM	Mediterranean	7d	86%	42% fungicide cost reduction	–	Martinez + 2024

Note: Lead = lead time; Acc. = accuracy; DM = downy mildew; ROI = return on investment. Economic values in original currencies.

When economic modelling integration is done, net benefits of AUD 47 million per year are observed in the 13 million hectare of the wheat area of production in Australia. Gain of (1) the difference between

seasons with low risk of Expectancy and those with low risk should be avoided by unnecessary application of fungicides (AUD 25 million); (2) acuteness of interventions in seasons with high expectations should exclude to avoid loss of yields (AUD 30 million); and (3) quality of grain following the reduction of disease pressure (AUD 8 million), should be partially compensated by the operational costs of the prediction system (AUD 16 million). Since 2022, the system is applied operationally using Grain Producers Australia, and transitioning capability (to adopting it at scale) has been successful.

DISCUSSION AND POLICY IMPLICATIONS

Implementation Challenges

Although the technical feasibility and economic possible applications have proven to be practical, there are numerous limitations to the extensive implementation of AI-based disease prediction systems. The limitations of data infrastructure, especially in developing areas, hinder model training as well as operational forecasting[42]. Smallholder farming zone areas are not adequately dense enough with weather stations to extract microclimate variability that is important in correct predictions. Weather estimates generated by satellites eliminate some gaps but usually cannot be as resolution as needed by diseases with responses to short-lasting events[20].

Digital divide on the availability of information denies the ability to make predictions that would be of maximum benefit to the farmers. Although the mobile phone penetration has gone up by quite a notably high margin, enabling delivery of information does not necessitate just connectivity but incorporates the interfaces to be farmer friendly, translate to local language, and to integrate with the extension support services[26]. As recorded by Martinez *et al.*[34], in Mediterranean areas, adoption of grapevine disease prediction system by farmers was significantly associated with extension agent engagement rather than prediction accuracy which is in contrast to sociotechnical implementation design.

The practical problems with model interpretability are the trustworthiness and suitable applications of the model by farmers. Deep learning black box systems are not easy to explain and explain, which could reduce the ability of farmers to trust prediction-driven decision-making[30]. Visualization, SHAP (SHapley Additive exPlanations) values, and their analogs represent somewhat useful solutions, but they need cautious translation to formats where planters can actually use them[55].

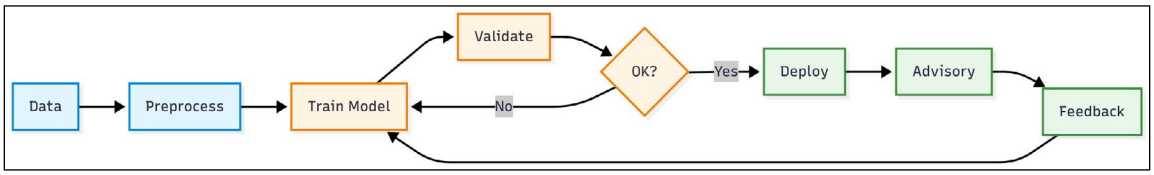

Fig. 4: Multi-scale disease prediction system integrating data collection, processing, decision-making, and feedback layers

Recommendations for Stakeholders

To researchers: The key areas of interest are: (1) creating transfer learning models that would allow

adapting the model to the data-poor areas through pre-training of data-rich region models[6]; (2) incorporating socioeconomic and farmer behaviour parameters into prediction-intervention systems[6]; (3) developing verification tests which quantify the result of actual decision-making, not the sole engineering prediction quality[6]; and (4) using uncertainty quantification.

For Policymakers: Investments should be made in: (1) the agricultural meteorological network densification of the main production regions; (2) the development of digital reporting systems for disease surveillance infrastructure and standardization; (3) the creation of predicting based integrated pest management regulatory frameworks that ensure environmental safety; and (4) public-private partnerships that are mutually beneficial in terms of sharing costs and benefits of prediction system development between the public research and private agricultural sectors [53].

In the case of Extension Services: The key areas of implementation encompass: (1) capacity building of extension agents to interpret prediction systems and formulate recommendations; (2) participatory design decision-making that involves farmer knowledge and preferences with the system comprises and incorporation; (3) generate information in conjunction with other system encompassing farm management; and (4) feedback loop, which allows farmers to report success and failure of the prediction systems and thereby system improvements are made[26].

Future Research Directions

There are a number of frontiers that should be explored. Multi-pathogen prediction models, which predict more than one disease in a given crop, could have a more comprehensive risk enhancement and may offer a means of optimal multi-target intervention scenarios[25]. The combination of genomic surveillance data on the evolution of the population of pathogens on the long-term track would optimize future predictions as the virulence profile changes[21].

Combined, the disease prediction models with climate change projections have the potential to identify the emerging regions at the high-risk areas and plans upon which adaptation should be carried out[8]. Breeding program priorities and agricultural policy could be informed through multi-year forward projections of trends in disease pressure through coupled climate-disease models that emphasize multi-year trends in disease pressure patterns[17]. This approach has been proven possible to the particular systems of Asian rice initially by Singh *et al.*[47] who predict a 15–20 percent rise in the number of days conducive to blast by 2050 assuming moderate climate change.

Edge computers, with a combination of computer vision, drone-based remote sensing, and autonomous field monitoring system would offer the high-resolution data used to train and validate the model as well as alleviate farmers of some workload [37]. Such technologies when linked to prediction systems would allow closed-loop adaptive management wherein predictions and observed requirements are used to dynamically adjust the intensity of monitoring and the predictions respectively.

CONCLUSION

The applications There is an emergent paradigm in agricultural disease management with enormous potential economic cost savings, fewer environmental deteriorations, and food security through AI-based seasonal forecasting of crop diseases. The most recent advancements in LSTM, TCN, and attention-based systems have shown prediction accurate of 80–90% in a lead time of 7–14 days of a variety

of crop-pathogen interactions, establishing actionable gap to act on preventative action plans. The economic analyses indicate possible returns on investment expenses of 300–500 which are propelled by a combination of the benefits of preserving yields, optimizing the expenses of inputs, and stabilizing the markets.

To actualise this potential, it is crucial to deal with major issues of implementation such as the development of data infrastructure, the level access to information, and the centred design to farmers. It is the ability of sociotechnical systems integration entailing embedding predictions in the richer environmental of agricultural decisions and not only the accuracy of technical prediction circa prediction that makes things straightforward. Data can be speeded up with strategic investment by both state and local governments in data systems, model development, and increased capacity so that maximum benefits can be experienced in the society.

With the intensified risks of diseases and the growing pressure on agriculture as a sustainability strategy emerging due to climate changes and the growing need to enhance sustainability and productivity through machine learning in agricultural contexts, the inevitable consequence is that AI-based prediction systems provide evidence-based opportunities to harmonize productivity, environmental responsibility, and economic feasibility. Further work on overcoming existing shortcomings, especially the generalizability of the models, the quantification of uncertainties, and multi-scale evaluation of economies will reinforce the root towards large scale operational applications thus improving resilient and sustainable agri-food systems across the world.

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