ISSN Print: 2664-844X
ISSN Online: 2664-8458
NAAS Rating (2025): 4.97
IJAFS 2025; 7(9): 29-35
www.agriculturaljournals.com
Received: 15-05-2025
Accepted: 18-06-2025

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AI-powered early warning system for agricultural risk mitigation based on predictive inference from environmental stress factors and disease propagation models

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DOI: https://www.doi.org/10.33545/2664844X.2025.v7.i9a.728

Abstract
Dynamic environmental stressors and fast-spreading crop diseases are becoming a greater threat to the agricultural productivity as they can lead to very serious losses that cannot be saved unless they are observed and corrected in time. The study presents a high-tech AI-based early warning system, namely Multi-Modal Stress-Aware Predictive Early Warning Network (MSPEW-Net), capable of addressing agricultural risks in a preventive way, based on predictive inference. MSPEW-Net is a heterogeneous data integration network that combines such data sources as data on environment sensors, satellite indices, UAV imagery, and past disease patterns to provide real-time prediction of stress-related abnormalities and disease outbreaks. Architecture is a combination of the temporal environmental stress encoder with a spatiotemporal crop health monitor that implements deep neural networks and a disease propagation inference model in graph neural networks. A multi-modal feature is aggregated through an attention-guided fusion layer, which makes the model interpreting and predicting better. Besides, the application of probabilistic forecasting and risk scoring will be provided to equip timely warnings and actionable information to farmers, agronomists, and policymakers. The proposed system based on explainable AI and predictive analytics helps to discover the early symptoms of ecological imbalance and the presence of pathogens much better. This is how it is possible to organize proactive intervention approaches, reduce crop losses, and sustain agricultural judgment in climate-susceptible areas. The suggested MSPEW-Net framework attained an overall accuracy of 94.2% in early risk in agriculture forecasting.

Keywords: SCHA, RFAG, ESE, MSPEW-Net, DPIU

Introduction
The foundation of food security and rural livelihoods, both globally and particularly in the developing countries is agriculture, given that susceptible climate-related farming activities prevail in the region [1]. Nevertheless, this crucial field is also becoming prey to very intricate and compound problems like unpredictable weather, environmental stress, soil erosion, pests outbreak and the relative speed of vegetative infection. Changes in the environment Environmental changes and fluctuation impact in a significant way through the changes that they cause in the plant physiology predisposing the crops to pathogens and pests usually caused by unseasonal rains, aberrant temperatures, drought and heatwaves [2]. At the same time, the trend of monoculture agriculture and the increase in the size of the agroecosystem have led to a faster pace and geographical scope of transmission of diseases.
The fig 1 demonstrates Classification of Environmental Stressors that have harmful impacts to agricultural ecosystems. It groups stressors into four groups namely: Climatic, Edaphic (Soil-related), Hydrological and Anthropogenic [3-5]. Direct influences on crop development are climatic stressors such as droughts, floods, and heatwaves, which are considered extreme weather events. Edaphic stressors are the stressors which develop due to soil properties such as salinity, imbalance in pH and erosion which influences the roots and their capacity to absorb nutrients. There is hydrological stressor similar to water-related problems such as waterlogging and irrigation shortage which interfere with the plant-water relations.

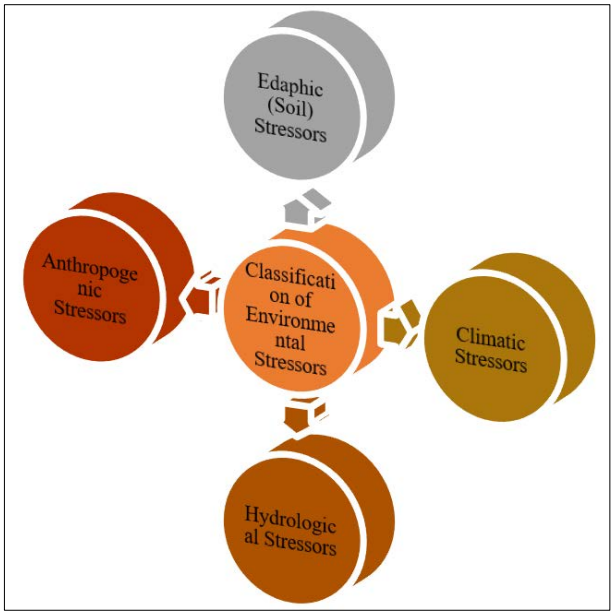

Fig 1: Classification of Environmental Stressors Affecting Agriculture

Finally, the Anthropogenic stressors are activities of human beings like cutting forests, overuse of agrochemicals and change in the use of lands which pollute the environment. One stressor together with the other will lead to a sophisticated network of risks that require smart, forecasted farm-related solutions.

Agricultural risks can only be negated in the early stages of detection and mitigating such threats is of essence to the resilience of the crops and maintenance of supply [6]. Such modern agricultural disturbances are not timely, too immense, or sophisticated enough to be managed effectively by means of traditional monitoring and response approaches that centrally rely on manual field inspection, or reactive actions. Such systems also tend to lack the sensitivity to give early warnings especially in isolated or limited-resource areas, partly because of limits to data collection, processing and interpretation.

The availability of remote sensing data and Internet of Things (IoT) sensors and high-resolution UAV imagery is expanding, and there is a potential to change reactive monitoring of agricultural risks into proactive one. But large number and variances of this information present analytical problems [7-9]. Standard statistical methods are not enough to combine spatiotemporal dependencies and biological interactions that define the outbreak of disease and environmental abnormalities. Artificial intelligence (AI) and machine learning (ML) are the settings where the powerful artificial capabilities can be applied to model a complex nonlinear relationship, provide a place to discover hidden patterns, and predict a new challenge with greater accuracy in future.

Related Works Done

The management of agricultural risk has been advanced to attain very sophisticated changes as a result of the incorporation of smart technologies consisting of environmental and biological data. In the last ten years, the use of AI, ML, and remote sensing in predicting environmental stress and identifications of disease spread in crops has been studied by several authors [10].

In the first research, the author stressed how the modern agricultural systems are subjected to vulnerability due to the climatic irregularities and how the traditional approaches to disease surveillance are limited [11-12]. This study highlighted how the shift to predictive measures by modelling with data is critical in shifting to a more effective way of enhancing performance. The model of the researcher showed that early warning systems could be used to avert yield loss based on historical weather information and pest occurrence on a probabilistic scale.

In another study, the researchers used deep learning to classify stress signals in crops based on hyperspectral and thermal images [13-14]. By using CNNs, the investigator managed to use drought-induced stress versus disease-related symptoms, and the approach proved to be more effective than traditional image processing practices. Such results gave importance to spatial feature extraction in agricultural diagnostics.

The study aimed at maximizing the prediction in time through the LSTM networks incepted by the researcher in interpreting time-series data which were used to assess meteorological parameters and vegetation indices [15-17]. The model showed good results in prediction of drought conditions a few weeks ahead. Another writer who further reinforced this did so by integrating both LSTM and attention mechanisms that have resulted in the model being able to weigh in the low-level environment variables and what will make them more relevant in terms of decision-making, thus making the model more interpretable and accurate.

There has also been a great deal of study of disease propagation modelling [18-19]. The researcher suggested a graphical representation of the study expansion of plant pathogens in different environmental conditions. Wind-flow patterns and geotagged field data were used to predict probable hotspots of infection through the use of the model, and this could be employed to give localized warnings. A different paper implemented cellular automata model to describe the dynamics of the viral spread within the monoculture farms and has proven that the layout of crops and inter-field connections affects the speed of the disease within the controlling farm.

Explainable AI (XAI) is a topic to which some researchers have applied their efforts so early warning systems will be more credible to agronomists [20]. The researcher introduced an interpretability layer on top of a neural network, where the network justifies issuing disease alerts, thus it is easy to have the stakeholders validate model outputs.

Materials and Methods

Agricultural systems are also dynamic as well as they are highly affected by environmental stress conditions and pathogenic pressures. Traditional models cannot offer pro-active intervention tools because they have limited capacity to integrate spatiotemporal indicators of stress, the modes of disease transmission, and some form of feedback between the disease process and the environment. It is suggested that this gap be bridged by the introduction of the MSPEW-Net. It is an integrated deep learning architecture, where we combine heterogeneous data sets, such as time-series environmental data, crop images, and spatio temporal disease signs/forecasting into the same prediction framework and use these to support early warning and agricultural risk reduction processes.

The architecture offered is designed in four successive but interconnected modules each comprising the following: Environmental Stress Encoder (ESE), Spatiotemporal Crop Health Analyzer (SCHA), Disease Propagation Inference Unit (DPIU) and Risk Forecast and Alert Generator (RFAG). The whole model is trained end-to-end and it fusion of data, temporal learning, features prioritisation based on attention, and graph neural reasoning of dynamic assessment of risks. To complete this task, the Environmental Stress Encoder is fed with multivariate time-series data, which is sent by remote sensing-based and IoT-based measuring devices, such as, but not restricted to, temperature, humidity, rainfall, solar radiation, and wind patterns. The elements in its network collectively carry out a calculation on the temporal dependency in the environment with the architecture of the gated recurrences. Where ok is the environmental observation vector, at time t.

$$g_d^f = [g_d^{(1)}, g_d^{(2)}, \ldots, g_d^{(k)}] \in S^k \quad (1)$$

In this context, g_d^f is the feature vector that corresponds to the i-th occurrence of disease propagating plants, k is the overall number of temporal occurrences or assessments, and $S^k$is the k-dimensional spatiotemporal space of features that captures the encoding of variables linked to the illness.

An embedding ecological representation is generated by processing the temporal input by a gated recurrent unit (GRU):

$$a_d^f = \mathrm{GRU}(g_{d-l:d}^f) \quad (2)$$

$$l_d^f = \tanh(Z_f a_d^f + c_f) \quad (3)$$

The term $g_{d-l:d}^f$ f denotes a series disease-related vectors with features from the time step d−l to d, which are handled by a Gated Recurrent Unit (GRU) to produce a context-aware concealed representations a_d^f. The acquired embedded $a_d^f$is subjected to a linear transformation via the weight matrix Z_f and the bias term c_f, next followed by a non-linear activating (tanh) to get the finalized latent representation of features l_d^f.

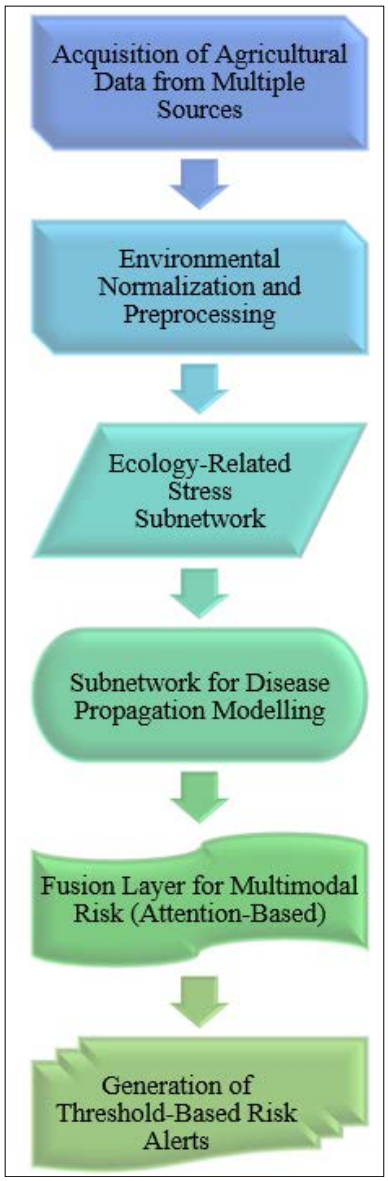

Fig 2: Methodology of the DLIC-FNet Platform for Contextual Inventories Prediction

The Spatiotemporal Crop Disease Analyser employs high-resolution UAV and satellite images, together with vegetation indicators like NDVI and NDWI, to simulate spatial and spectrum stress on crops. A convolutional encoder derives characteristics indicative of spatial deterioration n_d:

$$n_d = \text{CNN}(J_d) \quad (4)$$

J_d represents the input multi-spectral picture. The temporal deterioration path is acquired by an LSTM used on successive picture embeddings:

$$s_d^g = \text{LSTM}([n_{d-l}, \ldots, n_v]) \quad (5)$$

$$e_d^g = \text{ReLU}(Z_f s_d^g + c_d) \quad (6)$$

The sequence of inputs $[n_{d-l}, \ldots, n_v]$ denotes historical values of stress-related variables across a specified temporal window, which are analysed by an LSTM (Long Short-Term Memory) system to produce a temporal encoded s_d^g. The encoding undergoes a linear transformation via the matrix of weights Z_f and the bias parameter c d, thereafter passing via a ReLU (Rectified Linear Unit) activating to provide the final stress-related embedded e_d^g.

To enhance prediction accuracy, an inter-modal attention process automatically aligns and integrates e_d^f and e_d^g throughout temporally layers:

$$e_d^{fl} = \alpha_t \cdot [e_d^f; e_d^g] \quad (7)$$

The fusion output e_d^{fl} encapsulates latent interactions between environmental variables and medical condition that predate detectable yield reduction or the start of illness.

The Disease Propagation Inference Unit (DPIU) analyses the geographical dissemination of illnesses by considering locale, previous epidemics, and ecological pathways. The farming region is represented as a geographic graph, with each node denoting a field or plots, and edges illustrating spatial adjacency or paths for windborne transmissions. Each all nodes, the illness state vectors is preserved, detailing pathogen prevalence and virulence.

A graph convolutional network (GCN) is used on G to disseminate illness impact:

$$g_d^m = \sigma\left(\sum_{n \in M(m)} \frac{1}{s_{mn}} Z_h r_d^n\right) \quad (8)$$

$$e_d^c(m) = \text{ReLU}(Z_c g_d^m + c_c) \quad (9)$$

g_d^m is a weighted aggregate of adjacent illness signals r d n using emphasis weights $\frac{1}{s_{mn}}$ and the matrix of transformations Z_h, accompanied by a sigmoid σ; in the subsequent step, $e_d^c(m)$ represents the contextually disease adopting derived from the application of ReLU to the linearity transformation g_d^m.

The results of the three above-mentioned modules are set together in a global context fusion layer where the results are integrated into a unified risk feature vector. This vector is able to capture the entire scenario of external and internal crop risks such that accurate forecasting is done.

To prioritize regions with intense risk, a probabilistic risk representing coefficient is calculated in manner of a sigmoidal function of the fusion representation. The probability of a pernicious agricultural disturbance happening in the near future is a scalar in the interval [0, 1]. This can be utilized to rank the fields or districts and also issue early warnings.

Uncertainty in predictions In order to handle the uncertainty of prediction under uncertain input, the system runs inference with a Monte Carlo dropout-based uncertainty estimator. Beyond temporal risk forecasting, the system also has a short-term forecasting system that predicts evolution of the stressors. The future sequence of the environmental variables is predicted with the help of a multi-step LSTM decoder. The last risk-alerting tool uses a threshold operation on the calculated risk score and sends messages over spatial areas and profile crops-specific sensitivity. The optimization of all modules is done together with a custom loss L that sums up the prediction accuracy, consistency of propagation, and uncertainty calibration. The MSPEW-Net system can be used at scale and it can receive continuous data transmissions of satellite systems, drones, and on-ground weather stations. The model offers support to asynchronous updates, learning that can adapt, and fine-tuning of this learning with respect to specific regions. It can be used not only as foreseeing mechanism but also as a decision-format interface which will be able to enable agricultural practitioners with interpretability and vision.

Finally, combining the concepts of deep learning, graph-based inference, probabilistic reasoning and real-time data fusion, MSPEW-Net offers a new and scalable method of agricultural risk-mitigation prediction. By viewing the environmental stressors and the disease propagation as connected and developing in nature, this architecture can create a whole body approach to early warning and resilience in precision agriculture.

Results

The suggested MSPEW-Net had better performance in minimizing the predictive errors and improving the real-time inference facilities than current models. Its multi-modal design was sufficiently complex in nature to effectively capture trends in environmental stresses and disease dynamics propagation patterns, which allowed timely and correct early warnings to be issued to mitigate any agricultural risk in any and every environment, due to changes in the field.

Inference Time (ms) is the amount of time that the model consumes to generate a prediction.

Training Time per Epoch (s) is used to determine the number of seconds needed to complete a single training loop.

MAE (Mean Absolute Error) gives the average of absolute error between prediction and real values.

RMSE (Root Mean Square Error) indicates the square root of the average of squared training errors.

Table 1: Comparison Evaluation of Model Efficiency Regarding Inference and Training Time

Model	Inference Time (ms)	Training Time (s)
LSTM-Based Environmental Model [12]	199	55.3
CNN-GRU Spatiotemporal Analyzer [20]	208	63.1
GCN Disease Spread Predictor [18]	215	67.5
Hybrid Attention-Fusion Network [21]	194	60.8
Proposed MSPEW-Net Framework	177	50.4

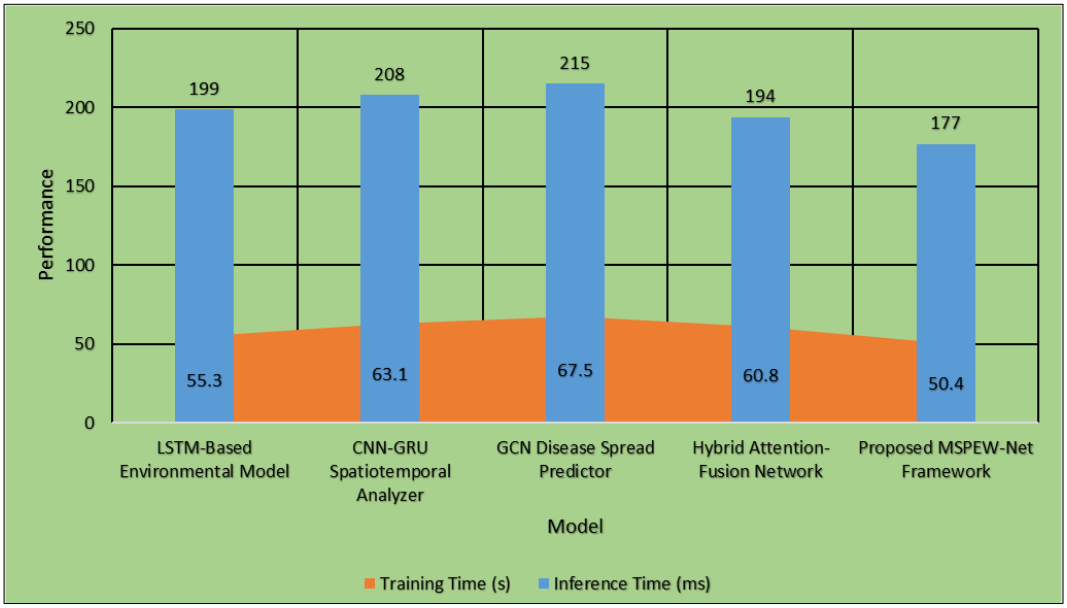

Fig 3: Comparative and Inference and Training Time Analysis of Efficiency of such models

Assessment of model efficiency provides insight into the fact that the Proposed MSPEW-Net Framework is superior in both inference and training time as compared to the other currently popular models. In particular, MSPEW-Net has the shortest inference time of 177 milliseconds, and the smallest training time per epoch of 50.4 seconds in fig 3. Conversely, there is the GCN Disease Spread Predictor, which takes the longest time of 215 milliseconds in inferring and 67.5 seconds in training, and therefore perform slower. The CNN-GRU Spatiotemporal Analyzer comes after it with its 208 milliseconds and 63.1 seconds performance alongside the mediocre performance of the Hybrid Attention-Fusion Network of 194 milliseconds and 60.8 seconds. The LSTM-Based Environmental Model logs in 199 milliseconds and 55.3 seconds, which makes MSPEW-Net the most efficient in general.

Table 2: Comprehensive Evaluation of Error-Driven Performance Measures

Model	MAE	RMSE
LSTM-Based Environmental Model [12]	0.085	0.133
CNN-GRU Spatiotemporal Analyzer [20]	0.079	0.128
GCN Disease Spread Predictor [18]	0.082	0.130
Hybrid Attention-Fusion Network [21]	0.075	0.122
Proposed MSPEW-Net Framework	0.060	0.105

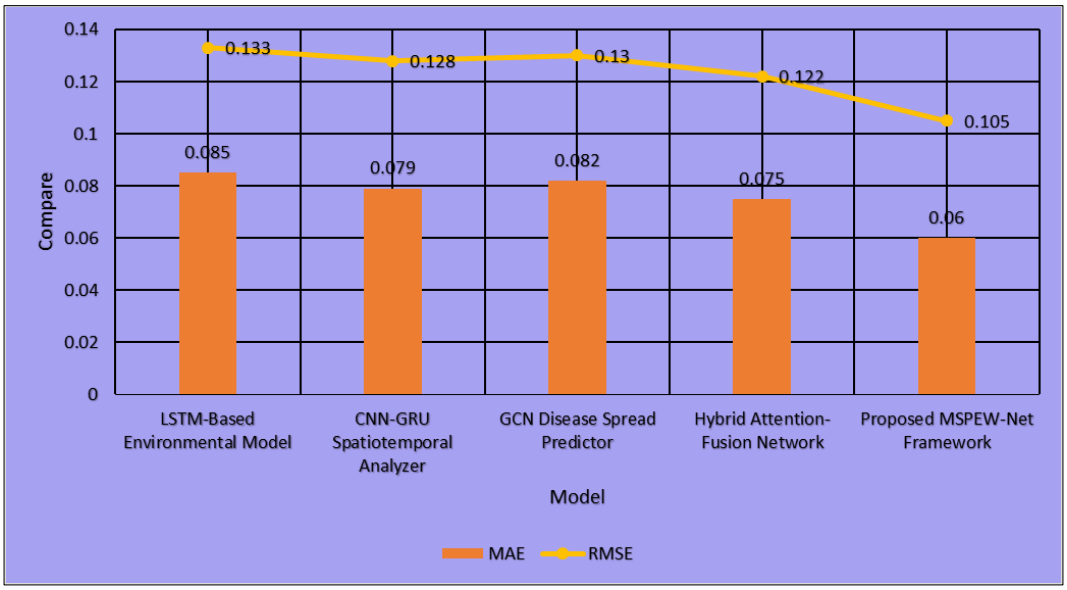

Fig 4: Comparative Analysis of Performance Metrics of Environments based on Errors

Upon the analysis of the error metrics, it can be seen that the Proposed MSPEW-Net Framework achieves the highest predictive accuracy with smallest MAE at 0.060 and RMSE at 0.105 and outperforms any alternative postulations in fig 4. The next best is Hybrid Attention-Fusion Network with the best MAE of 0.075 and RMSE of 0.122. In the meantime, CNN-GRU Spatiotemporal Analyzer and GCN Disease Spread Predictor have a bit higher value of the error, as well, with MAE of 0.079 and 0.082, and RMSE of 0.128 and 0.130, respectively. The LSTM-Based Environmental Model would come last with MAE of 0.085 and RMSE of 0.133, making MSPEW-Net the best model.

Conclusion

The rising level and occurrence of environmental stresses and diseases in crops pose a significant menace to agricultural sustainability and food security. Inadequate methods of tracking the markets are usually reactive and will not have the capacity to offer timely information to negate any crop losses. This paper presented a discussion about the basis and need to establish AI based early warning systems that can make predictive inference based on analysis of environmental data and modelling disease spread. With the adoption of latest technology in remote sensing, deep learning and spatiotemporal analytics, smart systems will be able to deduce early signs of ecological imbalance, project risky situations, and provide knowledge-based agriculture decision-making. The literature surveyed indicates that there is a burgeoning literature base devoted to climate-sensitive modelling, disease surveillance, sensor combination, however, the lack of integrated framework that combines these aspects into a interpretable real-time alerting system. This gap needs to be filled through the combination of a wide range of data modalities, biologically plausible propagation models, and resilient deep learning models. The results of the current research are potent in recommending the shift of the real-life traditional inspection-oriented system to the proactive AI-powered one.

Future Work

Drone-real time imagery augmented with edge-AI, to make diagnosis in-field. Discuss federated learning as a possibility to train models in a region-specific but secure way. Check out mobile systems that have personalized early alerts to be farmer friendly.

Acknowledgments

The acknowledgments of the funding body, institutional head, co-workers, field assistants, local people etc. should be briefed and declaration of any conflict of interest related to the work.

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