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HYBRID SPATIO-TEMPORAL DEEP LEARNING FRAMEWORK FOR EARLY PREDICTION OF ARECANUT FRUIT ROT DISEASE

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***Abstract.** Accurate early prediction of arecanut fruit rot disease remains difficult because disease outbreaks are governed by complex interactions among meteorological conditions, seasonal variability, and delayed pathogen responses. The progression of the disease is strongly influenced by spatio-temporal climatic patterns and biologically delayed environmental effects that conventional machine learning approaches often fail to represent effectively. This study proposes a biologically informed hybrid deep learning framework that integrates a ConvLSTM-based spatio-temporal learning module with a lag-aware tabular feature branch to jointly model spatial disease propagation, temporal climatic evolution, seasonal cyclicity, and delayed weather-driven responses associated with pathogen development. The framework was developed using weekly weather and disease intensity observations collected over two years from ten geographically distributed locations across four arecanut-growing districts of Karnataka, India. To improve forecasting capability, the methodology incorporates cyclic seasonal encoding, structured spatial weather-grid representation, and biologically meaningful lagged climatic features. A strict year-wise validation strategy was adopted, where the model was trained on one monsoon season and evaluated on an unseen season to assess real-world generalization performance. The proposed framework achieved a balanced accuracy of 0.9471 and a macro F1-score of 0.9257, outperforming conventional baseline models. The proposed methodology demonstrates strong potential as a transferable spatio-temporal forecasting framework for operational disease warning systems and AI-driven precision agriculture applications.

Keywords: Arecanut fruit rot, ConvLSTM, spatio-temporal modeling, lag-aware features, disease risk prediction, weather-based forecasting

1 Introduction

Arecanut (*Areca catechu* L.) is a major plantation crop in the coastal and Malnad regions of Karnataka, contributing significantly to the socio-economic stability of smallholder farmers. Fruit rot disease, primarily caused by *Phytophthora* species, poses a serious threat during the monsoon season, leading to substantial yield losses. The onset and progression of the disease are strongly influenced by rainfall, humidity, temperature fluctuations, and wind speed, often exhibiting delayed responses to favorable environmental conditions [1].

Traditional disease forecasting approaches rely on threshold-based rules or classical machine learning models that treat observations as independent samples. Such methods fail to capture the inherent spatial dependencies among locations and the temporal evolution of disease-favorable weather patterns. Recent advances in deep learning, particularly convolutional recurrent architectures, provide an opportunity to address these limitations by jointly modeling spatial and temporal dynamics.

This study presents a hybrid ConvLSTM-based spatio-temporal learning framework augmented with lag-aware tabular features for robust disease risk prediction. Unlike existing approaches, the proposed model explicitly incorporates spatial interactions between locations, delayed meteorological effects, and seasonal cyclic behavior, while being evaluated under a realistic year-wise forecasting scenario.

2 Literature Review

Recent advances in deep learning have significantly enhanced the modeling of complex spatio-temporal phenomena in climate, environmental monitoring, and agricultural forecasting. Several studies have explored architectures such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, graph neural networks (GNNs), and hybrid models to improve predictive performance.

2.1 Deep Learning for Climate and Environmental Forecasting

Guo *et al.* [2] conducted a comparative study of deep learning models for climate prediction and demonstrated that hybrid architectures outperform standalone models due to their ability to capture nonlinear temporal dependencies. However, their approach primarily focuses on temporal modeling and does not explicitly incorporate spatial interactions between geographic locations. Lee *et al.* [3] applied deep learning techniques to cloud cover prediction using satellite imagery. While their approach effectively captures spatial features, it lacks explicit modeling of lag-based temporal dependencies, which are crucial for representing delayed environmental responses. Tao *et al.* [4] utilized deep learning methods for typhoon track prediction, highlighting the

effectiveness of temporal sequence modeling. However, spatial dependencies are not explicitly modeled using structured representations such as grids or graphs.

2.2 Spatio-Temporal Modeling Approaches

Lira *et al.* [5] proposed a graph neural network with spatio-temporal attention for multi-source time series data. Although effective in capturing spatial relationships, GNN-based approaches require predefined graph structures, which may not be suitable for irregular agricultural datasets. Liao *et al.* [6] demonstrated the effectiveness of ConvLSTM models for flood prediction by integrating spatial and temporal dependencies. However, their approach does not incorporate domain-specific lag features to capture delayed environmental effects. Zhu *et al.* [7] conducted a comparative analysis of deep learning models for soil moisture prediction and emphasized the importance of spatio-temporal learning. Nevertheless, their work does not integrate tabular lag-based features with deep learning architectures.

2.3 Hybrid Deep Learning Models

Wu *et al.* [8] proposed a CNN–LSTM–attention hybrid model for landslide susceptibility prediction, achieving improved performance through combined spatial and temporal modeling. However, the model does not explicitly incorporate lag-based environmental features. Rajpoot and Chandrakar [9] developed a hybrid CNN–LSTM framework for crop yield prediction using spatio-temporal data. While effective, their work focuses on yield prediction rather than disease risk modeling and does not include lag-aware feature engineering. Sannasi *et al.* [10] introduced a hybrid spatio-temporal graph neural network combined with temporal convolutional networks for air quality prediction. Although the model performs well, it relies on graph structures that increase computational complexity.

2.4 Machine Learning in Environmental Risk Prediction

Zhang *et al.* [11] applied hybrid machine learning models for streamflow forecasting using real-time monitoring data. However, spatial dependencies are not explicitly modeled using structured spatial representations. Eaturu and Vadrevu [12] evaluated machine learning and deep learning models for fire prediction and demonstrated the importance of environmental variables. However, their approach treats observations independently and lacks spatial interaction modeling. Haque *et al.* [13] highlighted the importance of climate-driven early warning systems for infectious diseases. While providing valuable insights, the study primarily focuses on statistical models rather than deep learning-based spatio-temporal frameworks. Ou Ali *et al.* [13] proposed hybrid deep learning models for energy prediction, demonstrating improved performance through model integration. However, spatial dependencies are not considered in their framework.

3 Study Area and Dataset Description

The dataset comprises weekly observations collected from ten geographically distributed monitoring locations across four major arecanut-growing districts of Karnataka, India: Dakshina Kannada, Chikkamagaluru, Davanagere, and Shivamogga. These districts represent diverse agro-climatic environments ranging from high-rainfall humid coastal ecosystems to moderate-rainfall inland transitional zones, thereby providing substantial spatial and climatic heterogeneity for weather-driven disease forecasting. The inclusion of geographically diverse locations improves the robustness and generalizability of the proposed forecasting framework under varying environmental conditions.

Two years of field surveillance and meteorological observations were compiled for this study during the biologically active monsoon period associated with arecanut fruit rot disease development. Data were collected at weekly intervals from each monitoring location, where every observation corresponds to a unique location-week pair containing synchronized disease intensity and climatic measurements.

Disease severity was quantified using Percent Disease Intensity (PDI) obtained through weekly field surveillance conducted at each study location. Meteorological variables corresponding to the same observation period were collected from nearby weather monitoring sources and included rainfall (mm), maximum temperature ($^{\circ}\text{C}$), minimum temperature ($^{\circ}\text{C}$), relative humidity (%), wind speed (km h^{-1}), and water temperature ($^{\circ}\text{C}$). Geographic coordinates (latitude and longitude) were additionally incorporated to preserve spatial dependency information required for spatio-temporal modeling.

To focus specifically on the period most relevant to disease initiation and progression, only monsoon-season observations recorded between May and November were retained for analysis. After temporal aggregation and harmonization across two monsoon seasons, the initial dataset consisted of 560 location-week observations ($10 \text{ locations} \times 56 \text{ weekly observations}$). Following lag-feature generation and spatio-temporal sequence construction, observations lacking sufficient historical temporal context were excluded prior to model training.

The resulting structured multi-location dataset provides a suitable foundation for modeling delayed climatic responses, seasonal variability, and spatial disease propagation using the proposed lag-aware hybrid ConvLSTM framework.

Table 1. Geographic distribution and agro-climatic characteristics of study locations

District	Location ID	Latitude	Longitude	Agro-climatic significance	Number of Weekly Observations
Chikkamagaluru	L1	12.989100	75.276199	High-rainfall hilly moisture zone	56
Dakshina Kannada	L2	12.762298	75.200258	Humid coastal monsoon region	56
Dakshina Kannada	L3	12.556100	75.393204	High-humidity coastal disease zone	56
Dakshina Kannada	L4	12.767845	75.100214	Heavy-rainfall coastal agriculture	56
Shivamogga	L5	13.610000	75.509804	Transitional malnad climate	56
Shivamogga	L6	13.537700	75.354202	Moderate-rainfall inland zone	56
Chikkamagaluru	L7	13.426900	75.255096	Elevated moist agro-climatic region	56
Davanagere	L8	14.025200	75.925697	Semi-humid inland cultivation zone	56
Davanagere	L9	14.240500	75.648598	Transitional moderate-rainfall area	56
Davanagere	L10	14.515400	75.810799	Variable monsoon inland region	56
Total	10	—	—	—	560

4 Methodology

The proposed framework integrates spatio-temporal deep learning with biologically informed lag-aware climatic analysis for early prediction of arecanut fruit rot disease. Unlike conventional forecasting approaches that primarily rely on independent climatic observations or short-term temporal relationships, the proposed methodology is specifically designed to capture delayed environmental responses, seasonal climatic cyclicity, and spatial synchronization of disease-favorable conditions across geographically distributed cultivation regions.

Disease development in arecanut plantations is strongly influenced by cumulative and delayed climatic effects such as persistent rainfall, prolonged canopy wetness,

elevated humidity, and sustained moisture conditions during the monsoon season. To model these biologically meaningful delayed responses, lag-aware climatic variables are incorporated into the framework to represent temporal dependencies associated with pathogen incubation and disease progression.

The overall workflow of the proposed methodology consists of sequential preprocessing, spatial representation, temporal sequence construction, hybrid feature learning, and multiclass disease-risk prediction stages, as illustrated in Fig. 1. Initially, weekly meteorological observations collected from multiple locations are temporally harmonized, normalized, and seasonally encoded using cyclic transformations to preserve periodic monsoon behavior. The geographically distributed observations are subsequently transformed into structured spatial weather grids using latitude–longitude mapping, enabling representation of regional climatic continuity and spatial disease propagation patterns.

To capture evolving spatio-temporal climatic interactions, consecutive weather-grid snapshots are processed using a ConvLSTM-based learning branch capable of jointly modeling spatial dependencies and temporal environmental evolution Guo et al. [19]. Simultaneously, biologically meaningful lagged climatic variables are processed through a dense feature-learning branch to capture delayed weather-driven effects associated with disease initiation and progression. The extracted representations from both branches are refined through global average pooling and feature-fusion operations to integrate spatial, temporal, seasonal, and lag-aware climatic information within a unified forecasting framework.

Finally, the fused representation is passed through a softmax classification layer to predict multiclass disease-risk categories corresponding to low-, moderate-, and high-risk disease conditions. This integrated framework therefore enables biologically informed forecasting of climate-driven disease outbreaks by simultaneously modeling delayed climatic responses, spatial disease synchronization, and temporal environmental evolution across diverse agro-climatic regions.

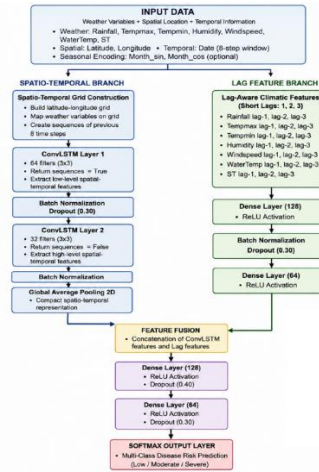


Fig.1. Methodology

4.1 Data Preprocessing and Feature Engineering

Prior to model development, the collected meteorological observations were subjected to preprocessing to ensure temporal consistency, numerical stability, and suitability for spatio-temporal learning. Since climatic observations obtained from field monitoring and weather stations may occasionally contain missing or incomplete records, missing values within each location-specific time series were handled using linear interpolation followed by backward and forward filling to preserve temporal continuity and avoid disruption of sequential climatic patterns.

To minimize scale-related bias among heterogeneous meteorological variables and improve convergence stability during deep learning optimization, all continuous climatic features were normalized using Min–Max scaling. This transformation rescales each feature to the range $[0, 1]$, thereby preventing variables with larger numerical magnitudes from dominating the learning process [24,25].

$$x' = \frac{-x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

Where in Equation (1)

x represents the original climatic feature value,

$x_{\min}$ and $x_{\max}$ denote the minimum and maximum values of the corresponding feature computed from the training dataset,

x' represents the normalized feature value.

The normalization process was applied independently to all meteorological variables, including rainfall, temperature, humidity, wind speed, and water temperature.

4.1.1 Seasonal Cyclic Encoding:

Fruit rot disease development in arecanut plantations is strongly associated with monsoon-driven seasonal variability. Climatic conditions favorable for pathogen growth, including prolonged rainfall, persistent canopy moisture, and elevated humidity, exhibit cyclic temporal behavior across months. Representing months as ordinary categorical or integer variables can introduce artificial discontinuities in temporal learning. For example, December (12) and January (1) are temporally adjacent but numerically distant when encoded directly.

To preserve the periodic continuity of seasonal transitions, cyclic seasonal encoding was performed using sine and cosine transformations of the month variable:

$$\text{Month}_{\sin} = \sin\left(\frac{2\pi m}{12}\right), \quad \text{Month}_{\cos} = \cos\left(\frac{2\pi m}{12}\right) \quad (2)$$

Where in Equation (2) $m \in \{1, 2, \dots, 12\}$

$\text{Month}_{\sin}$ and $\text{Month}_{\cos}$ represent cyclic seasonal encodings preserving temporal periodicity.

This transformation enables the forecasting model to learn smooth seasonal transitions and recurring monsoon-associated climatic patterns more effectively than conventional categorical month representations.

4.1.2 Lag Feature Generation:

The epidemiology of arecanut fruit rot disease is governed by delayed environmental responses rather than instantaneous climatic conditions alone. Disease outbreaks frequently occur after sustained exposure to favorable environmental conditions such as continuous rainfall, prolonged humidity retention, canopy wetness, and moisture accumulation. These delayed effects are associated with pathogen incubation, sporulation, infection establishment, and subsequent disease progression.

To explicitly model these biologically meaningful delayed climatic influences, lag-aware meteorological features were generated from historical weather observations. Lag variables allow the framework to capture temporal dependencies between antecedent climatic conditions and disease manifestation at future observation periods.

The lag-feature formulation is expressed as:

$$X_t^{(lag-k)} = X_{t-k}, k \in \{1, 2\} \quad (3)$$

Where in Equation (3)

X_t denotes the climatic variable observed at time step t ,

X_{t-k} represents the historical climatic observation recorded k time steps before the current observation,

k denotes the temporal lag interval,

$X_t^{lag(k)}$ represents the lag-transformed climatic feature used for forecasting disease risk at time t .

Lag intervals were selected to capture short-term and intermediate delayed climatic responses associated with disease development dynamics during the monsoon season. These lagged representations enable the model to learn cumulative environmental influences linked to pathogen activation, incubation behavior, and delayed symptom emergence, thereby improving biologically informed disease forecasting performance.

4.2 Spatial Grid Construction

One of the key methodological contributions of the proposed framework is the transformation of irregular geographically distributed agro-climatic observations into structured spatial tensors suitable for convolution-based spatio-temporal learning. Since weather observations are collected from discrete monitoring locations distributed across multiple districts, the raw geographic data do not naturally possess the structured neighborhood representation required for convolutional neural networks (CNNs) and

ConvLSTM operations. In climate-driven disease systems, neighboring cultivation regions often experience similar monsoon dynamics, humidity conditions, rainfall persistence, and temperature fluctuations. Consequently, disease outbreaks may exhibit spatial synchronization and regional propagation patterns rather than isolated point-wise behavior. Capturing these geographically correlated climatic interactions is therefore essential for accurate disease forecasting.

To preserve spatial continuity and neighborhood-level environmental relationships, each monitoring location was mapped onto a fixed spatial grid using latitude–longitude ordering. This transformation converts irregular multi-location climatic observations into structured spatial weather tensors where adjacent grid cells correspond to geographically related cultivation regions. Such representation enables convolutional operations to learn localized spatial dependencies and regional climatic interactions associated with disease development.

Figure 2. illustrates the complete spatial mapping procedure, including:

- (i) original geographic distribution of monitoring locations,
- (ii) latitude–longitude-based spatial indexing, and
- (iii) transformation into structured multi-channel spatial tensors for ConvLSTM processing.

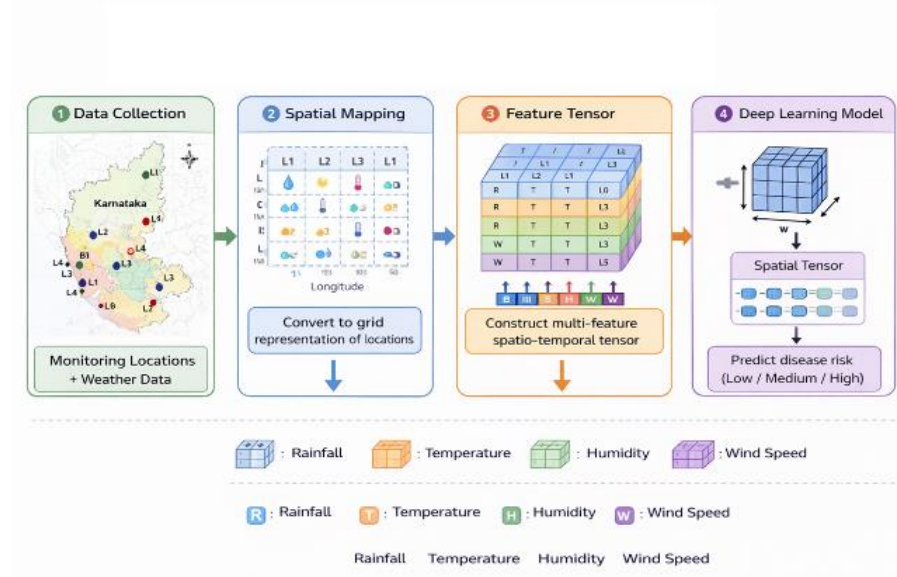


Fig.2. Spatial mapping to multi-channel tensor workflow

For each observation period, a multi-channel spatial weather grid was constructed in which every grid cell represents a specific monitoring location and contains normalized meteorological variables associated with that location. The spatial tensor representation is defined as:

$$\mathbf{G} \in \mathbb{R}^{H \times W \times C} \quad (4)$$

Where in Equation (4)

$\mathbf{G}$ denotes the structured spatial weather tensor,

H and W represent the spatial grid height and width, respectively,

C denotes the number of climatic feature channels included in each grid cell.

Each spatial location within the tensor contains a feature vector composed of normalized meteorological variables:

Each grid cell $\mathbf{G}_{i,j}$ represents a location with feature vector:

$$\mathbf{G}_{i,j} = [r, T_{max}, T_{min}, RH, WS] \quad (5)$$

where in Equation (5)

$\mathbf{G}_{i,j}$ represents the climatic feature vector corresponding to grid position (i, j) ,

r denotes rainfall,

T_{max} denotes maximum temperature,

T_{min} denotes minimum temperature,

RH denotes relative humidity,

WS denotes wind speed.

This structured representation enables convolutional kernels to extract neighborhood-level climatic interactions across adjacent geographic regions. The convolution operation applied over the spatial tensor is expressed as:

$$\mathbf{F}_{i,j} = \sum_{u,v} \mathbf{K}_{u,v} \cdot \mathbf{G}_{i+u,j+v} \quad (6)$$

Where in Equation (6)

$\mathbf{F}_{i,j}$ denotes the extracted spatial feature at grid position (i, j) ,

$\mathbf{K}_{u,v}$ represents the convolution kernel weight at neighboring position (u, v) ,

$\mathbf{G}_{i+u,j+v}$ denotes neighboring climatic observations surrounding the target grid cell.

Through this operation, the framework learns localized spatial climatic dependencies and geographically synchronized environmental patterns associated with disease propagation. The resulting structured spatial representation therefore enables effective integration of geographic continuity, neighborhood climatic influence, and regional disease dynamics within the proposed spatio-temporal forecasting framework.

4.3 Spatio-Temporal Sequence Formation

Plant disease development is inherently dynamic, where environmental conditions from preceding weeks collectively influence pathogen activation, moisture accumulation,

infection initiation, and subsequent disease progression. Consecutive weekly observations are therefore important because climatic continuity—particularly sustained rainfall, prolonged humidity, and persistent canopy wetness—creates favorable conditions for gradual disease establishment rather than instantaneous outbreaks. To capture these evolving temporal dependencies, sliding windows of consecutive weekly observations were used to construct spatio-temporal sequences Liu et al. [20].

For each prediction time step t , the model receives a sequence of spatial weather grids representing climatic evolution over four consecutive weeks:

$$\mathcal{X}_t = \{G_{t-3}, G_{t-2}, G_{t-1}, G_t\} \quad (7)$$

where in Equation(7)

G_t denotes the spatial weather grid at week t ,

t represents the current observation week,

$\mathcal{X}_t$ represents the ordered temporal sequence of spatial climatic observations used for forecasting disease risk.

This sequential representation enables the ConvLSTM framework to learn how disease-favorable environmental conditions evolve and propagate spatially across neighboring geographic locations over time.

Accordingly, the spatio-temporal input tensor is represented as:

$$\mathcal{X} \in \mathbb{R}^{T \times H \times W \times C} \quad (8)$$

Where in Equation (8)

T : number of temporal steps (weeks) in the sequence,

H : spatial grid height representing latitude-wise location arrangement,

W : spatial grid width representing longitude-wise location arrangement,

C : number of meteorological feature channels associated with each location.

The tensor therefore preserves both temporal continuity and spatial neighborhood relationships simultaneously, enabling the model to capture climate-driven disease synchronization patterns across regions.

In addition to the spatial sequence tensor, lag-aware climatic features were incorporated through a parallel tabular branch to explicitly model delayed environmental responses associated with pathogen incubation and moisture persistence. The lag-based feature vector is defined as:

$$\mathbf{Z}_t = [\mathbf{X}_t, \mathbf{X}_{t-1}, \mathbf{X}_{t-2}] \quad (9)$$

Where in Equation (9):

$\mathbf{X}_t$: climatic feature vector at the current week t ,

$\mathbf{X}_{t-1}$: climatic observations from the previous week,

$\mathbf{X}_{t-2}$: climatic observations from two weeks prior.

The combined use of spatio-temporal sequences and lag-aware climatic features enables the framework to jointly model spatial disease propagation, temporal climatic

evolution, and biologically delayed disease responses within a unified forecasting architecture.

4.4 Hybrid ConvLSTM Tabular Architecture

The proposed framework integrates spatio-temporal sequence learning with lag-aware climatic modeling through a dual-branch deep learning architecture. The overall design was motivated by the biological behavior of arecanut fruit rot disease, where disease emergence depends not only on current environmental conditions but also on delayed climatic effects and spatial synchronization of favorable weather conditions across neighboring regions.

The architecture therefore combines:

1. ConvLSTM-based spatio-temporal branch for learning spatial propagation and temporal climatic evolution, and
2. Dense tabular branch for explicitly modeling delayed weather responses using lag-based climatic variables.

The outputs from both branches are subsequently fused to generate multiclass disease-risk predictions (low, moderate, and high risk).

4.4.1 ConvLSTM Branch

The ConvLSTM branch processes sequential spatial weather tensors to capture both Spatial correlations among geographically neighboring locations, and Temporal evolution of disease-favorable climatic conditions across consecutive weeks.

Unlike conventional LSTM networks that use fully connected operations, ConvLSTM replaces matrix multiplications with convolution operations, thereby preserving spatial neighborhood information during temporal learning Kilinc et al. [21].

This is particularly important for agricultural disease forecasting because nearby regions often experience synchronized rainfall, humidity persistence, and moisture accumulation patterns that collectively influence disease propagation.

The ConvLSTM operations are defined as:

$$\mathbf{i}_t = \sigma(\mathbf{W}_i * \mathbf{X}_t + \mathbf{U}_i * \mathbf{H}_{t-1} + \mathbf{b}_i) \quad (10)$$

Similarly, the full ConvLSTM equations are:

$$\mathbf{f}_t = \sigma(\mathbf{W}_f * \mathbf{X}_t + \mathbf{U}_f * \mathbf{H}_{t-1} + \mathbf{b}_f) \quad (11)$$

$$\mathbf{C}_t = \mathbf{f}_t \odot \mathbf{C}_{t-1} + \mathbf{i}_t \odot \tanh(\mathbf{W}_c * \mathbf{X}_t + \mathbf{U}_c * \mathbf{H}_{t-1}) \quad (12)$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_o * \mathbf{X}_t + \mathbf{U}_o * \mathbf{H}_{t-1}) \quad (13)$$

$$\mathbf{H}_t = \mathbf{o}_t \odot \tanh(\mathbf{C}_t) \quad (14)$$

Where in Equations (11,12,13,14):

$\mathbf{X}_t$: input spatial weather tensor at time step t ,

H_t : hidden state representing learned spatio-temporal features,
 C_t : memory cell state,
 i_t, f_t, o_t : input, forget, and output gates,
 W and U : convolution kernels,
 $*$: convolution operation,
 $\odot$: element-wise multiplication,
 σ : sigmoid activation function.

The forget gate selectively retains long-term climatic information, while the input gate incorporates newly observed environmental conditions. This mechanism enables the model to learn delayed climatic influences associated with disease incubation and progressive pathogen development.

4.4.2 Layer-wise Architecture Interpretation

The ConvLSTM branch contains two stacked ConvLSTM layers.

- The first ConvLSTM layer learns broad spatio-temporal climatic interactions such as regional rainfall synchronization and humidity continuity.
- The second ConvLSTM layer extracts higher-level disease-relevant temporal representations from the learned spatial patterns.

Batch normalization layers are applied after ConvLSTM operations to stabilize feature distributions during training and improve convergence. Dropout regularization is introduced to reduce overfitting caused by strong temporal correlations in climatic observations.

Global Average Pooling is subsequently applied to compress high-dimensional spatial feature maps into compact feature representations while preserving dominant climatic activation patterns. This reduces model complexity and improves generalization performance. ConvLSTM branch architecture is displayed in Table 2.

Table 2. ConvLSTM branch architecture

Layer	Filters / Units	Kernel Size	Activation	Functional Role
Input	(T x H x W x C)	–	–	Sequential spatial weather tensors
ConvLSTM2D	64	(2 x 2)	ReLU	Learn primary spatio-temporal climatic interactions
Batch Normalization	–	–	–	Stabilize feature distributions
Dropout	0.30	–	–	Reduce overfitting
ConvLSTM2D	32	(2 x 2)	ReLU	Extract higher-level disease patterns
Batch Normalization	–	–	–	Improve training stability

Global Average Pooling	–	–	–	Compress spatial feature maps
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4.4.3 Lag-Aware Tabular Branch

Although ConvLSTM effectively captures spatio-temporal climatic evolution, disease development is also strongly influenced by delayed environmental effects that may not be fully represented through spatial sequence learning alone.

To explicitly model antecedent climatic influences, a parallel dense neural network branch was constructed using lag-based weather variables.

The lag-feature representation is processed as:

$$\mathbf{h} = \phi(\mathbf{W}\mathbf{Z}_t + \mathbf{b}) \quad (15)$$

where *in* **Equations (15)**:

$\mathbf{Z}_t$: lag-based climatic feature vector,

$\mathbf{W}$: trainable weight matrix,

$\mathbf{b}$: bias term,

ϕ : nonlinear activation function (ReLU),

$\mathbf{h}$: learned lag-aware feature representation.

This branch captures delayed rainfall accumulation, sustained humidity persistence, and incubation-related climatic responses associated with pathogen activation.

Table 3. Lag-Aware Tabular Branch Architecture

Layer	Units	Activation	Functional Role
Input	Lag feature vector	–	Historical climatic observations
Dense	64	ReLU	Learn delayed climatic interactions
Batch Normalization	–	–	Stabilize dense feature learning
Dropout	0.20	–	Prevent overfitting
Dense	32	ReLU	Generate compact lag-aware representation

4.4.4 Feature Fusion and Disease Classification

The outputs of the ConvLSTM branch and lag-aware dense branch are concatenated through a feature-fusion layer before final classification. This fusion strategy is important because the two branches learn complementary information:

The ConvLSTM branch captures spatial synchronization and temporal climatic evolution. The dense lag branch explicitly models delayed biological responses and antecedent environmental effects.

By combining both representations, the framework simultaneously learns:

- Regional climatic propagation,
- Temporal disease progression,
- Delayed pathogen response dynamics,
- and localized environmental memory effects.

The fused representation is passed through fully connected layers and a softmax output layer to generate multiclass disease-risk predictions corresponding to low-, moderate-, and high-risk disease categories.

4.5 Implementation details

To prevent information leakage during model development, the dataset was first partitioned into training and testing subsets prior to preprocessing. Min–Max normalization parameters were estimated exclusively from the training subset and subsequently applied to the testing subset using the same scaling coefficients.

Table 4. Implementation details

Parameter	Value
Programming language	Python
Deep learning library	TensorFlow / Keras
Data processing	Pandas, NumPy
Feature scaling	MinMaxScaler
Oversampling	SMOTE
Optimizer	Adam
Learning rate	default Adam
Loss	Focal loss
Epochs	100
Batch size	32
Validation split	20%
Early stopping patience	15
Random seed	42

5 Experimental Result

To preserve the temporal integrity of disease forecasting and avoid information leakage, a strict year-wise validation strategy was adopted. The model was trained using observations from one cultivation year and evaluated on an entirely unseen year. This setup simulates realistic operational forecasting conditions where future disease outbreaks must be predicted using historical climatic observations.

Meteorological variables were normalized using Min–Max scaling prior to model training. Missing observations were handled using location-wise temporal interpolation followed by backward and forward filling to maintain continuous climatic sequences. Spatial weather tensors were constructed from latitude–longitude ordered locations, enabling the ConvLSTM branch to learn geographic disease propagation patterns.

Simultaneously, lag-based tabular features representing delayed climatic responses were processed through a dense neural branch.

The model was implemented using TensorFlow and trained using the Adam optimizer with an initial learning rate of 10^{-3} . Early stopping and adaptive learning-rate reduction were applied to prevent overfitting and stabilize convergence. Batch normalization and dropout regularization were incorporated throughout the architecture to improve generalization performance.

5.1 Evaluation Metrics

Model performance was evaluated using Balanced Accuracy, Macro F1-score, ROC-AUC, confusion matrix analysis, and prediction visualization. These metrics were selected to provide reliable evaluation under imbalanced disease-risk distributions.

$$\text{Accuracy} = \frac{1}{2} \left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP} \right) \quad (16)$$

Where in Equation (16):

TP : true positives

TN : true negatives

FP : false positives

FN : false negatives

Macro F1-score was computed as:

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (17)$$

where in Equation (17) precision and recall evaluate the balance between false positives and false negatives across disease-risk classes.

Additionally, ROC-AUC analysis was performed to evaluate the model's discriminative capability across different classification thresholds.

5.2 Training Stability Analysis

Figure 3 illustrates the training and validation loss curves observed during model optimization. Both losses decrease rapidly during the initial epochs and gradually converge toward stable minima, indicating effective learning of climatic disease patterns. The validation loss closely follows the training loss throughout the optimization process, suggesting minimal overfitting and strong generalization capability. Only minor fluctuations are observed during later epochs, demonstrating stable convergence behavior and robustness of the proposed hybrid architecture.

The incorporation of batch normalization, dropout regularization, focal loss optimization, and early stopping contributed significantly to training stability under imbalanced disease conditions.

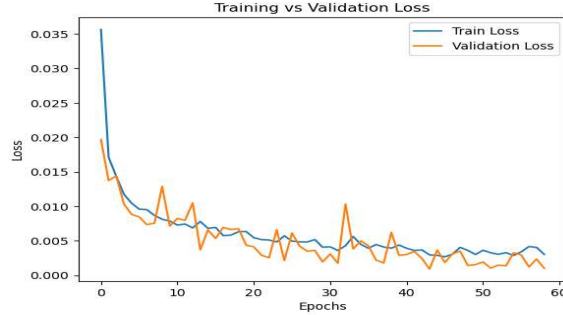


Fig.3. Training vs validation loss

5.3. Lag Correlation Analysis

Lag correlation analysis was performed to investigate delayed climatic influences on disease intensity. The analysis revealed that rainfall exhibits increasing positive correlation at lag-1, lag-2 and lag-3 intervals, indicating that disease severity is more strongly associated with antecedent moisture conditions than with immediate rainfall events.

This delayed response aligns with the biological progression of *Phytophthora* infection, where sustained moisture accumulation, canopy wetness, and prolonged humidity create favorable conditions for pathogen incubation and disease spread. Similar delayed trends were also observed for relative humidity and temperature-related variables. The results validate the biological relevance of lag-aware feature engineering incorporated within the proposed framework.

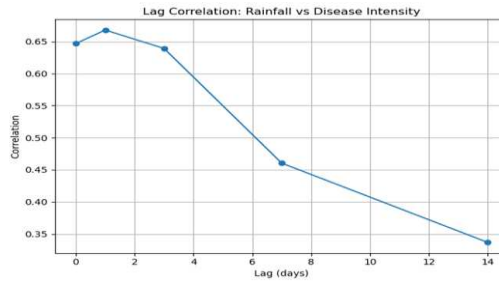


Fig. 4. Lag correlation between rainfall and disease intensity

5.4 ROC-AUC Analysis

Figure 5 presents the ROC curve obtained for disease-risk classification. The proposed model achieved an AUC value of 0.997, indicating near-perfect separation between disease-risk classes.

The curve remains substantially above the random baseline across all thresholds, confirming the robustness and sensitivity of the proposed architecture in identifying both low-risk and high-risk disease conditions.

The high ROC–AUC performance demonstrates the effectiveness of combining spatial-temporal learning with lag-aware climatic modeling.

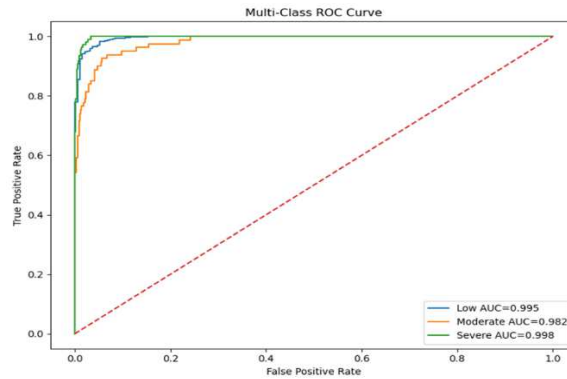


Fig. 5. Multi-class ROC curve

5.5 Confuion Matrix Analysis

Figure 6 presents the confusion matrix obtained on the unseen test dataset. Most samples were correctly classified, with minimal misclassification between risk categories.

The model correctly identified 628 low-risk, 60 moderate samples and 102 high-risk samples, while only a small number of observations were incorrectly classified. The low false-negative rate is particularly important for agricultural disease forecasting because missed high-risk outbreaks may lead to severe crop losses. These findings confirm that the proposed framework maintains balanced sensitivity and specificity across multiple disease-risk levels.

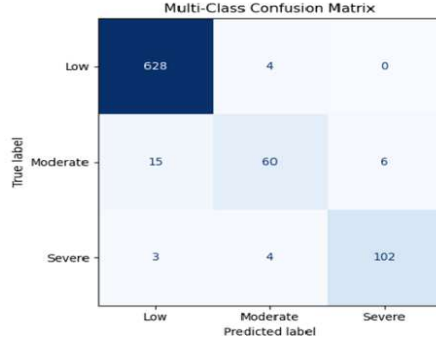


Fig. 6. Confusion Matrix

5.6 Prediction VS Actual Analysis

Figure 7 compares predicted disease-risk labels against actual observations. The predicted outputs closely follow the true disease patterns, indicating that the model successfully captures temporal disease evolution and climatic variability across locations. The close agreement between predicted and observed disease conditions further demonstrates the reliability of the proposed spatio-temporal forecasting framework.

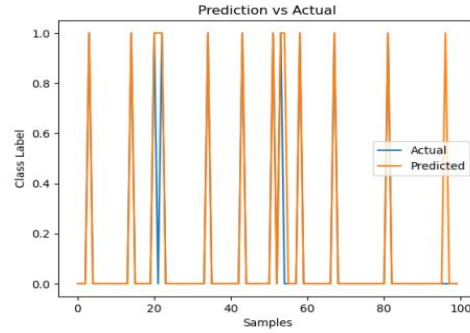


Fig. 7. Prediction vs Actual sample

5.7 Comparative Analysis

To evaluate the proposed approach, traditional models—Logistic Regression, Random Forest, and Gradient Boosting, LSTM, CNN-LSTM, ConvLSTM —were trained using lag-based weather features without spatial data. As shown in Table 5, the proposed hybrid model outperformed all, highlighting the advantage of spatio-temporal learning.

Table 5. Baseline Model Performance Comparison

Model	Description	Balanced Accuracy	Macro F1-score	ROC-AUC
Logistic Regression	Linear baseline model	0.7421	0.7013	0.8125
Random Forest	Ensemble tree-based model	0.8615	0.8352	0.9023
XGBoost	Gradient boosting model	0.8847	0.8629	0.9286
LSTM	Temporal sequence modeling	0.9012	0.8845	0.9458
CNN-LSTM	Spatial + temporal hybrid	0.9186	0.9021	0.9612
ConvLSTM (Only)	Spatio-temporal learning	0.9314	0.9136	0.9725
Proposed Hybrid Model	ConvLSTM + Lag-aware features	0.9471	0.9257	0.9873

5.8 Ablation Study

To analyze the contribution of individual components in the proposed hybrid framework, a comprehensive ablation study was conducted by systematically removing or modifying major architectural modules. The experiments evaluated the importance of the ConvLSTM spatio-temporal branch, lag-aware climatic features, feature fusion mechanism, seasonal cyclic encoding, and lag-selection strategy.

Table 6 presents the performance comparison of different ablation variants using Balanced Accuracy, Macro F1-score, and ROC-AUC metrics.

Table 6. Ablation Study Results

Model Variant	Balanced Accuracy	Macro F1	ROC-AUC
Full Hybrid Model	0.9471	0.9257	0.9873
Without ConvLSTM	0.7804	0.7900	0.9546
Without Lag Features	0.7425	0.6689	0.9115
Without Feature Fusion	0.7450	0.6688	0.9100
Without Seasonal Encoding	0.8657	0.8773	0.9883
Long Lags Instead of Short Lags	0.8636	0.8786	0.9894
ConvLSTM Only	0.7201	0.6612	0.9099
Lag Branch Only	0.7665	0.7759	0.9489

The results demonstrate that the complete hybrid framework consistently achieved the best overall performance, confirming the complementary contribution of both spatio-temporal learning and lag-aware climatic modeling.

Removing the ConvLSTM branch caused a noticeable reduction in Balanced Accuracy and Macro F1-score, indicating the importance of spatial and temporal dependency learning across geographically distributed locations. Similarly, eliminating lag-based climatic features significantly degraded performance, demonstrating that delayed meteorological effects play a critical role in disease progression modeling.

The feature fusion mechanism also contributed substantially to predictive performance, as models without fusion exhibited reduced classification capability. Seasonal cyclic

encoding provided additional contextual information regarding monsoon-driven disease dynamics, though its removal caused only a moderate decrease in performance.

The comparison between short biological lags (1–3 weeks) and long lags (1, 3, 7, 14 weeks) revealed that short lags produced more stable and biologically relevant predictions, supporting the hypothesis that recent climatic conditions exert stronger influence on disease initiation and spread.

Overall, the ablation analysis confirms that the superior performance of the proposed framework arises from the synergistic integration of:

- ConvLSTM-based spatio-temporal learning,
- lag-aware climatic feature engineering,
- seasonal cyclic encoding, and
- hybrid feature fusion.

6 Results and Discussion

The proposed hybrid ConvLSTM framework achieved a balanced accuracy of 0.9471 and a macro F1-score of 0.9257, and a ROC–AUC score of 0.9873 on the unseen test dataset, demonstrating strong predictive capability for multi-class arecanut fruit rot disease risk classification. The high ROC–AUC value indicates the model’s strong ability to effectively discriminate among different disease-risk categories under varying climatic conditions.

The superior performance of the proposed framework can be attributed to three major methodological factors: (i) effective learning of spatial and temporal climatic interactions through ConvLSTM-based spatio-temporal modeling, (ii) incorporation of biologically meaningful lag-aware meteorological features representing delayed environmental effects associated with disease development, and (iii) integration of complementary feature representations through the hybrid feature-fusion architecture. Unlike conventional machine learning approaches, which treat each observation independently, the proposed framework explicitly models evolving climatic dependencies across both space and time.

The ablation study further confirmed the contribution of individual architectural components. Removal of the ConvLSTM branch, lag-aware feature branch, or feature fusion mechanism resulted in noticeable reductions in Balanced Accuracy and Macro F1-score, demonstrating that both spatial–temporal learning and lag-based climatic representation are essential for accurate disease-risk prediction. Similarly, the comparison between short-term and long-term lag strategies showed that biologically relevant short lags (lag-1, lag-2, and lag-3) produced more stable and discriminative predictions than longer lag intervals.

Although the proposed framework achieved strong classification performance, several limitations remain. The model depends on accurate spatial representation of geographic locations and requires moderate computational resources for ConvLSTM training. In addition, the study was conducted using data collected from a limited number of locations and seasons. Future work may focus on incorporating longer multi-year datasets, integrating additional environmental variables such as soil moisture and remote sensing

indicators, and improving model interpretability using explainable AI techniques for operational deployment in precision agriculture and disease early-warning systems

7 Conclusion

This study presents a hybrid ConvLSTM-lag feature fusion framework for climate-driven prediction of arecanut fruit rot disease by jointly modeling spatial climatic variability, temporal weather evolution, seasonal cyclicity, and delayed environmental effects within a unified deep learning architecture. By integrating structured spatial weather-grid construction, cyclic seasonal encoding, biologically meaningful lag-aware feature engineering, ConvLSTM-based spatio-temporal sequence learning, and dual-branch feature fusion, the proposed framework provides an effective modeling pipeline for agricultural disease forecasting.

Experimental evaluation demonstrates that the framework successfully learns stable predictive representations, effectively captures delayed climatic influences associated with disease progression, and achieves strong multi-class classification performance. The proposed hybrid architecture achieved a balanced accuracy of 0.9471 and a macro F1-score of 0.9257, and a ROC-AUC score of 0.9873, outperforming conventional machine learning baselines. The ablation study further confirmed the importance of ConvLSTM-based spatio-temporal learning, lag-aware climatic features, seasonal encoding, and feature fusion in improving predictive performance.

The proposed framework is computationally reproducible, scalable, and transferable to other climate-sensitive forecasting applications involving multi-location temporal observations. With minimal adaptation to input variables and domain-specific targets, the methodology can be extended to broader agricultural disease early-warning systems and environmental spatio-temporal prediction tasks. Overall, this work provides a reusable deep learning framework for developing next-generation AI-driven decision-support systems in precision agriculture

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Ethical approval: This study did not involve human participants, animals, or clinical trials. Therefore, ethical approval was not required.

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Consent to publish: Not applicable.

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Data Available Statement

Supporting data are available from the corresponding author on request.

References

1. Patil, B., Chittaragi, A., Loona, D., Hosagoudar, G.N., Prathibha, V.H., Mohan, M., Hurakadli, M.S., Pandian, R.T.P., Thube, S.H., Hegde, V. and Naik, M.K. (2025), Weather-Driven Dynamics of Fruit Rot Disease in Arecanut—A Time Series Approach Using ARIMA and SARIMA Models. *Plant Pathol*, 74: 2412-2426. <https://doi.org/10.1111/ppa.70034>.
2. Rajashree Krishna and KV Prema, “Constructing and optimizing RNN models to predict fruit rot disease incidence in areca nut crops based on weather parameters,” *IEEE Access* (2023)
3. Guo, Q., He, Z., Wang, Z., Qiao, S., Zhu, J., & Chen, J. (2024). A Performance Comparison Study on Climate Prediction in Weifang City Using Different Deep Learning Models. *Water*, 16(19), 2870. <https://doi.org/10.3390/w16192870>. (Guo et al., 2024)
4. Lee, Y., Min, S., Yoon, J., Ha, J., Jeong, S., Ryu, S., & Ahn, M.-H. (2024). Application of deep learning in cloud cover prediction using geostationary satellite images. *GIScience & Remote Sensing*, 62(1). <https://doi.org/10.1080/15481603.2024.2440506>
5. Tao, C., Wang, Z., Tian, Y., Han, Y., Wang, K., Li, Q., & Zuo, J. (2024). Calibration of Typhoon Track Forecasts Based on Deep Learning Methods. *Atmosphere*, 15(9), 1125. <https://doi.org/10.3390/atmos15091125>
6. Lira, H., Martí, L., & Sanchez-Pi, N. (2022). A Graph Neural Network with Spatio-Temporal Attention for Multi-Sources Time Series Data: An Application to Frost Forecast. *Sensors (Basel, Switzerland)*, 22(4), 1486. <https://doi.org/10.3390/s22041486>
7. Liao, Y., Wang, Z., Yu, H., Gao, W., Zeng, Z., Li, X., & Lai, C. (2025). Accelerating Urban Flood Inundation Simulation Under Spatio-Temporally Varying Rainstorms Using ConvLSTM Deep Learning Model. *Water Resources Research*, 61(8). <https://doi.org/10.1029/2025wr040433>
8. Zhu, L., Dai, W., Huang, J., & Luo, Z. (2024). A comparative analysis of deep learning models for accurate spatio-temporal soil moisture prediction. *Geocarto International*, 40(1). <https://doi.org/10.1080/10106049.2024.2441382>
9. Bunyang, S., Thedwichienchai, N., Pintong, K., et al. Self-supervised learning advanced plant disease image classification with SimCLR. *Advances in Computational Intelligence*, 3, 18 (2023). <https://doi.org/10.1007/s43674-023-00065-z>.
10. Wu, H., Niu, J., Li, Y., Wang, Y., & Qiu, D. (2025). Landslide Susceptibility Prediction Based on a CNN–LSTM–SAM–Attention Hybrid Model. *Applied Sciences*, 15(13), 7245. <https://doi.org/10.3390/app15137245>
11. Rajpoot, S., & Chandrakar, O. (2025). A hybrid CNN-LSTM deep learning framework for enhanced crop yield prediction using spatial-temporal agricultural data. *International*

- Journal of Statistics and Applied Mathematics*, 10(12S), 01–09.
<https://doi.org/10.22271/math.2025.v10.i12sa.2200>
12. Sannasi, P., P, S., & R, S. (2025). STGNN-TCN: Hybrid Model for Spatiotemporal Air Quality Prediction based on Spatio-Temporal Graph Neural Networks and Temporal Convolutional Networks. 993–999. <https://doi.org/10.1109/icaiss61471.2025.11042243>
 13. Zhang, Y., Zhou, Z., Deng, Y., Pan, D., Van Griensven Thé, J., Yang, S. X., & Gharabaghi, B. (2024). Daily Streamflow Forecasting Using Networks of Real-Time Monitoring Stations and Hybrid Machine Learning Methods. *Water*, 16(9), 1284. <https://doi.org/10.3390/w16091284>
 14. Eaturu, A., & Vadrevu, K. P. (2025). Evaluation of machine learning and deep learning algorithms for fire prediction in Southeast Asia. *Scientific Reports*, 15(1), 18807. <https://doi.org/10.1038/s41598-025-00628-9>.
 15. Haque, S., Mengersen, K., Barr, I., Wang, L., Yang, W., Vardoulakis, S., Bambrick, H., & Hu, W. (2024). Towards development of functional climate-driven early warning systems for climate-sensitive infectious diseases: Statistical models and recommendations. *Environmental Research*, 249, 118568. <https://doi.org/10.1016/j.envres.2024.118568>
 16. Ou Ali, I. H., Agga, A., Ouassaid, M., Maaroufi, M., Elrashidi, A., & Kotb, H. (2024). Predicting short-term energy usage in a smart home using hybrid deep learning models. *Frontiers in Energy Research*, 12. <https://doi.org/10.3389/fenrg.2024.1323357>
 17. Sharma, M., & Jindal, V. (2023). Approximation techniques for apple disease detection and prediction using computer-enabled technologies: A review. *Remote Sensing Applications: Society and Environment*, 32, 101038. <https://doi.org/10.1016/j.rsase.2023.101038>
 18. J. S., D. E., V. Ramalingam, I. Venkatachalam, M. Vivekanandan, and M. R., "An Efficient Detection and Classification of Plant Diseases using Deep Learning Approach," 2023 International Conference on Evolutionary Algorithms and Soft Computing Techniques (EASCT), Bengaluru, India, 2023, pp. 1-6, doi: 10.1109/EASCT59475.2023.10393829.
 19. Guo, A., Liu, Y., Shao, S., Shi, X., & Feng, Z. (2025). Spatial-Temporal Fusion Graph Neural Networks With Mixed Adjacency for Weather Forecasting. *IEEE Access*, 13, 15812–15824. <https://doi.org/10.1109/access.2025.3532473>.
 20. Liu, H., Liu, J., Hu, T., & Ma, H. (2026). Spatio-Temporal Probabilistic Forecasting of Wind Speed Using Transformer-Based Diffusion Models. *IEEE Transactions on Sustainable Energy*, 17(1), 184–196. <https://doi.org/10.1109/tste.2025.3591920>.
 21. Kilinc, H. C., Apak, S., Ergin, M. E., Ozkan, F., Katipoğlu, O. M., & Yurtsever, A. (2025). Enhancing hydrological time series forecasting with a hybrid Bayesian-ConvLSTM model optimized by particle swarm optimization. *Acta Geophysica*, 73(4), 3549–3566. <https://doi.org/10.1007/s11600-025-01570-0>.
 22. Nasaruddin, N., Masseran, N., Idris, W. M. R., & Ul-Saufie, A. Z. (2025). A SMOTE PCA HDBSCAN approach for enhancing water quality classification in imbalanced datasets. *Scientific Reports*, 15(1), 13059. <https://doi.org/10.1038/s41598-025-97248-0>
 23. Husain, G., Nasef, D., Jose, R., Mayer, J., Bekbolatova, M., Devine, T., & Toma, M. (2025). SMOTE vs. SMOTEENN: A Study on the Performance of Resampling Algorithms for Addressing Class Imbalance in Regression Models. *Algorithms*, 18(1), 37. <https://doi.org/10.3390/a18010037>.
 24. S. Sridhar, M. Vijayalakshmi, Machine learning (pp. 869–959). (2024). Elsevier eBooks. <https://doi.org/10.1016/b978-0-32-391772-8.00019-3>.
 25. Hastie, Trevor & Tibshirani, Robert & Friedman, Jerome & Franklin, James. (2004). The Elements of Statistical Learning: Data Mining, Inference, and Prediction. *Math. Intell.*, 27, 83–85. 10.1007/BF02985802.

26. Shalev-Shwartz, S., & Ben-David, S. (2014). Understanding Machine Learning: From Theory to Algorithms. Cambridge University Press.