RESEARCH PAPER

# Cotton pest and disease multi-class classification with weather and temporal predictors features across Indian agroclimatic zones

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**ABSTRACT**
The Pink Bollworm (Pectinophora gossypiella) remains one of the most destructive pests affecting cotton productivity, with infestation levels strongly driven by climatic fluctuations and crop phenology. This study presents a machine learning–based framework for early multi-classification and prediction of Pink Bollworm incidence using agro-meteorological variables. The dataset includes maximum and minimum air temperature, relative humidity, rainfall, sunshine hours, evaporation, and wind speed, all of which influence Pink Bollworm development, migration, and reproductive cycles. After preprocessing, applying cyclic encoding to temporal variables, and generating lagged climatic features, multiple machine learning algorithms—including SVM, Neural Networks, KNN, Regression models, Ensemble methods, and Naïve Bayes—were trained and systematically compared. SVM model demonstrated the best test accuracy, effectively capturing dynamic climate–pest interactions. The resulting MATLAB-based classification tool enables rapid assessment and supports climate-informed pest surveillance. A stratified 80:20 train-test split was employed, with 5-fold cross-validation on the training set for hyperparameter tuning, ensuring no data leakage between partitions. The validation and training accuracies of these models are 89.4% and 96 % respectively. Overall, the model offers a practical and interpretable solution for early detection of Pink Bollworm risk, thereby contributing to informed decision-making in integrated pest management (IPM) and precision agriculture.
**Keywords:** Machine Learning, Pest Classification, Gradient Boosting, Temporal Features, Pest Forecasting, Multi-class Classification.
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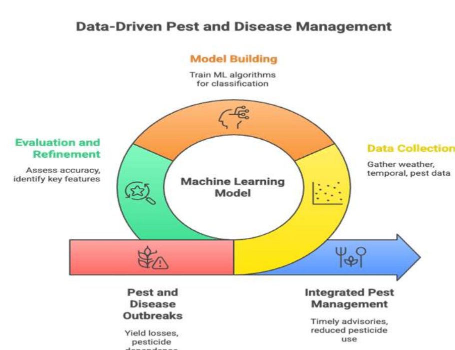
## 1 Introduction

A key factor driving the dynamics of agricultural pests and diseases is the variability in meteorological parameters and temporal effects (Shafique et al. 2025). Disease spread, migration and pest population growth are influenced strongly by rainfall, humidity, and temperature fluctuations (Liakos et al. 2018; Arachchillage et al. 2020). An effective, as-needed and proactive pest control strategy depends on accurate forewarning and predictive weather-based models (Naranammal and Priya 2024; Sadhana et al. 2025). Such models would contribute towards optimal pesticide usage by the farmers by offering them adequate lead time on weather dyanmics affecting their crops (Solke et al. 2022; Kanwal et al. 2022; Luttrell et al. 1994).




*Data-Driven Pest and Disease Management*

The conventional statistical models are proving inadequate in predicting the increasingly dynamic weather phenomena, hence necessitating adoption of novel approaches involving machine learning and deep learning based computational intelligence in prediction of agro-meteorological events (Yadav and Singh 2020; Maxwell et al. 2018). Recent research studies emphasise the applicability and suitability of the modern machine learning approaches as compared to the generalized linear models or the multiple regression based statistical techniques for pest predictions (Trapero et al. 2016; Durgabai et al. 2018). Studies have shown that the population growth, incidence and spread of pests such as Whiteflies, Aphids, Thrips and Jassids that affect cotton crops can be accurately forecasted using ensemble machine learning and long short-term memory (LSTM) networks (Kaur et al. 2021; Kumar et al. 2024). Pest-infested disease identification, pest detection, as well as round-the-clock farm monitoring can be automated through IoT applications that integrate sensor fusion and artificial intelligence (Soofi and Awan 2017; Kotsiantis et al. 2006; Purohit et al. 2021).

There is evident scope for developing a robust framework that simultaneously classifies and models temporally complex weather phenomena in real time (Thenmozhi and Reddy 2019). Most of the studies reported in the available literature have targeted a single pest and/or pest induced crop disease for modeling and prediction (Hussain et al. 2023). The present study aimed to achieve a concurrent classification of cotton crop related pests and pest induced diseases using multiple temporal and weather data parameters. This study explored the efficacy of multi classification machine learning architectures to target multiple kinds of pests affecting cotton crops (Taran et al. 2022a). This approach ensures a more comprehensive forwarning system that would actually prove useful to the farmers and promote precision agriculture practices based on real time farming data (Michie et al. 1995; Attri et al. 2024).

*Pink Bollowen (TNAU Agritech Portal 2025)*

Cotton production in the Indian states of Telangana, Gujarat and Maharashtra have been advesely impacted by the Pink Bollworm (Pectinophora gossypiella) (Parmar and Patel 2016). Over the last decade, this pest has developed resistance against pest control measures employed by farmers in cotton fields. Improper refuge implementation and climatic shifts have contributed towards recurring outbreaks of PBW despite the Bt cotton crop adoption in many farms (Irfan et al. 2025). Yield losses of upto 40% have been reported owing to the PBW infestations, wherein the PBW pest larvae cause irreversible damage of the cotton seeds and lints by boring into the cotton balls. Moreover, the PBW pests exhibit diapause behavior during cooler months of the year, and are able to persist in their attacks over multiple generations. Hence, a robust multiclass pest classification requires an integration of annual and monthly PBW occurence datasets to ensure effective early detection and prediction pest control architectures in Indian cotton farming (Gutierrez et al. 2015). The data-driven pest disease management system proposed in this study is shown in Figure 1.

Degree-day models estimate pest development by accumulating heat units above a fixed temperature threshold, an approach that performs reasonably well under uniform conditions but fails when field conditions intervene (Bansode and Deshmukh 2018). These models are inherently single-variable and single-target, unable to account for the combined influence of humidity, rainfall, and seasonal shifts, and incapable of distinguishing between co-occurring pests and diseases within a single predictive framework (Saleem et al. 2021). Across India's diverse agroclimatic zones, where multiple cotton pests emerge simultaneously under complex, interacting environmental conditions, this architectural limitation renders bioclimatic models fundamentally unsuitable for multi-class pest advisory systems (Taran et al. 2022b; Sharma et al. 2024). Machine learning overcomes this not by refining the degree-day logic, but by learning nonlinear relationships across multiple weather and temporal variables simultaneously, producing probabilistic classifications across all relevant pest and disease categories in a single unified model (James and Das 2022; Patel and Shah 2025).

This study integrated multi-pest disease labels, variable temporal spans (seasons, weeks, months) and weather data classify multiple pests/diseases in the Indian context (Chiewchan Kitti 2019). The present work relied upon the cotton disease and pest datasets available in the public domain for machine learning modeling. Multiple algorithms such as the Naive Bayes, ensemble, regression, KNN, neural networks and support vector machines (SVM) were explored and compared in terms of their classification accuracies (Ben Bahri et al. 2020; Anita Gutta 2012). The modeling approach adopted in this study ensured the effective identification of the most dominant parameter contributing/related to pest induced diseases in cotton crops (Shah et al. 2022; Dietterich 2000). Such multi-class machine learning approaches are required in an integrated pest management system that provides timely actionable insights and decision support to the India cotton farmers combating pest menace (Al Shamisi et al. 2011).

The major contributions of the present study are listed below:

1. Cotton crop disease and pest multi class classification modeling based on weather and agricultural data.
2. Effective prediction of seasonal pest dynamics using engineered lagged feature based modeling using temporal weather data.
3. Insights into the effects of different weather conditions on pest and disease occurrence and proliferation based on classification results.
4. Identification of the SVM architecture as the most accurate and effective machine learning approach for multi class classification of cotton crop pests/diseases based on temporally varying weather data.

The crop pest/disease classification approach adopted in the present study has the potential to minimize cotton crop losses and promote sustainable robust farming in Indian conditions (Kasinathan and Uyyala 2021). The following section presents a brief review of the literature published on this topic.

## 2 Literature Review

A lot of research efforts are being focused on pest and crop disease prediction owing to evolving pest behaviors and climate variations that are leading to significant crop yield losses in the agricultural sector. Limited on ground detection and diagnostic resources traditionally rely on expert visual inspection and manual scouting, which are time intensive, subjective and particularly ineffective in case of large farms (Bock et al. 2010). Researchers support and promote the deployment of artificial intelligence based solutions that are driven by actual farm data and help mitigate crop threats in a timely manner.

### 2.1 Existing Pest and Disease Prediction Models

Initial research investigations in this field relied upon rule based and statistical models for forecasting crop infestations. Investigators usually employed poisson, logistic or linear regression methods to model environmental data against pest incidence and population growth (Yonow and Kriticos 2014). However, these modeling approaches could not account for the increasing non linearities in the evolving agricultural and weather dynamics.

Machine learning models, on the other hand, became increasing preferred in modeling complex agricultural system dynamics. In particular, the support vector machines were applied by researchers in this field owing to their robustness in higher dimensional datasets (Naeem et al. 2017). SVM was shown to yield higher accuracy of predicting different crop attacking pests such as cotton ballworm, rice blast and whitefly among others.

Researchers have also explored artificial neural networks to model the non linear behavior of crop disease outbreak and severity patterns. In particular, the radial basis function networks and the multi layer perceptrons have been successful in predicting crop infestation parameters (Singh and Misra 2017). However, neural networks tend to be computationally intensive and require larger datasets for accurate predictions, which restricts their suitability for larger scale applications.

On the other hand, the K-Nearest Neighbours (KNN) algorithm has a simpler architecture leading to better results even with medium and even small sized datasets. KNN has been successfully used to classify insect presence and fungal leaf disease symptoms using limited agricultural datasets (Barbedo 2013). However, noisy datasets prove detrimental to KNN accuracy. Moreover, it is difficult to suitably apply KNN for scalable applications.

Researchers have also favored the gradient boosting machines and random forest algorithms for generalizing the complex feature interactions associated with the multi-parameter agro-meteorological datasets. Ensemble learning methods are also popular for their multi-parameter handling characteristics. The XGBoost method has achieved high prediction accuracy of varying crop disease conditions with remarkable training efficiency (Sharma et al. 2020).

In some cases, the Naive Bayes classifiers have been used to explore inter-feature correlation assumptions for enhancing predictive modeling results. Naïve Bayes models remain computationally efficient and useful in real-time decision support systems, despite being generally less accurate than ensemble methods (Chen and Zhang 2016; Yu et al. 2025).

### 2.2 Use of Meteorological and Temporal Variables in Prediction

Pest induced crop diseases are prominently influenced by multiple meteorological parameters such as the intensity of solar radiation, wind speed, rainfall, humidity and temperature variations. Research studies try to include as many climate variables as possible to ensure robust predictions. However, certain factors are more prominent than others, such as temperature and humidity, which were found to have more significant impact on powdery mildew, a fungal disease. On the other hand, aphids and leaf miners pest infestations were most impacted by wind patterns and rainfall (Ponomareva et al. 2020).

In addition to the above, pest infestations are also affected by temporal variables such as growing degree days, months, week number and even particular day of the year. The crop specific phenological stages also depend on seasons and thus impact pest life cycles. Researchers have tried to include some of these temporal features to further improve infestation outbreak occurrences, fluctuations and general patterns (Jiang et al. 2019; Jiang et al. 2025). However, some studies did not integrate these temporal features with the environmental factors discussed before, thus restricting their predictive efficacy and applicability to complex agricultural scenarios.

### 2.3 Identified Research Gaps

Primarily, the following research gaps can be delineated in this field:

1. **Lack of Multi-Class Classification Approaches** - Most of the research investigations in the field of crop disease prediction include just two classes - absence or presence of a particular crop disease or pest. Only a few studies have attempted simultaneous multi class approaches to overcome the limitations of binary classification for efficient differentiation of different types of diseases and pests that affect crops (Rumpf et al. 2010). Hence, the absence of a multi-class approach remains an open research problem to be explored.
2. **Limited Integration of Temporal and Weather Features** - Researchers have addressed the temporal and weather related features individually for crop disease predictions. However, comprehensive modeling requires a consideration of both these feature types, along with their complex interaction effects for robust classification performance (Zhang et al. 2020).
3. **Insufficient Region-Specific Datasets** - Most published research on this subject is focused on crop disease modeling on data gathered from local geographical regions located outside India. Such models cannot be effectively generalized to Indian farm conditions. Effective modeling of crop diseases in Indian field conditions require own geography-specific agricultural and weather trend databases across the nation's varying climatic zones (Ghosh and Baidya Roy 2020).

In a nutshell, the published literature emphasizes the usage of machine learning based methods over conventional linear regression techniques to better classify crop pestilence. Moreover, multi-class classification is the need of the hour over binary classification approaches usually adopted by the researchers. Finally, both meteorological as well as temporal variables must be considered for a more robust and comprehensive detection and classification of multiple crop diseases caused by pests.

This study was designed to overcome all of the above discussed gaps in research of plant diseases due to pestilence occurrences. The machine learning framework proposed in the present study incorporates temporal and weather data features to provide a multi class classification solution. The present work employed advanced feature engineering strategies in ensemble learning architectures to enhance classification accuracy. The overall aim of the study was to provide a meaningful, timely and accurate scalable solution for India's cotton crop disease detection needs.

## 3 Dataset

The foundation of this study is a novel, aggregated agro-ecological time-series dataset, designed specifically for modeling and classification of the Pink Bollworm (Pectinophora gossypiella) lifecycle and severity in cotton agroecosystems. This dataset comprises of various environmental condition parameters and spans over multiple years (Singh 2023). Table 1 depicts these parameters along with their specific relevance in multi class classification carried out in the present study.

*Description of Agro-meteorological Variables Used in Pest/Disease Classification*

| Variable Name | Full Description | Unit | Role in Predictive Modeling |
|---|---|---|---|
| MaxT | Maximum Air Temperature | °C | Drives developmental rate and heat unit accumulation for pest life stages. |
| MinT | Minimum Air Temperature | °C | Influences nocturnal insect activity, moth flight, and diapause induction signals. |
| RH1, RH2 | Relative Humidity Readings (Morning | % | Quantifies diurnal moisture oscillation, relating to egg |

| Variable Name | Full Description | Unit | Role in Predictive Modeling |
|---|---|---|---|
| | and Evening) | | viability, fungal infection risk, and desiccation vulnerability. |
| RF | Total Rainfall | mm | Hydrological modulator influencing larval wash-off, field moisture availability, and disease spread conditions. |
| EVP | Total Evaporation | mm | Proxy for plant moisture stress and atmospheric water demand affecting pest–host interactions. |
| SSH | Total Sunshine Hours | hrs | Correlates with solar energy input, canopy thermal load, and photosynthesis-related microclimatic effects. |
| WS | Average Wind Speed | kmph | Affects adult moth dispersal, transport patterns, and spatial pest movement (requires preprocessing for zero-value sequences). |

The dataset was cleaned by removing all geographical identifiers, so that the predictive modeling could be generalized over the selected agro-ecolgical relationships. One of the useful features of this dataset is that it provides a longitudinal structure of temporal aggregation in terms of its adherence to the Standard Meteorological Week (SMW) index (1–52). It is a consistent scale of temporal markers that supports advanced pest classification and forecasting by incorporating seasonal crop development phases. Table 2 shows the multi class labels corresponding to the different types of the pink bolloworm pest that afflicts cotton crops in India.

*Unique Categories (Pink Bollworm)*

| No. | Pest/Disease Type | Unit / Observation Basis |
|---|---|---|
| 1 | PinkBollworm-Larva | (Number/ 20 green bolls) |
| 2 | PinkBollworm-Adult | (Number/ Pheromone trap) |
| 3 | PinkBollworm-Damage | (Percent boll damage) |
| 4 | PinkBollworm-Damage | (Percent flower damage) |
| 5 | PinkBollworm-Larva | (% larval population /100 bolls) |
| 6 | PinkBollworm | (Number/ Pheromone trap) |

The weekly entomological data was synchronized with the data of eight continuous environmental variables shown in Table 1 for predictive modeling of the pest classes shown in Table 2.

## 4 Methodology

This study presents a multi class classification of pest diseases affecting cotton crops in the Indian context. It utilizes weekly agro-meterological data for predictive modeling that included feature engineering, Matlab-based application integration, model development and classification explainability analysis.

*Methodology pipeline for weather–temporal based multi-class pest/disease prediction using machine learning.*

The dataset considered for modeling in this study included multiple environmental parameters. These included wind speeds, sunshine hours, evaporation rate, rainfall intensity, relative humidity during the mornings and evenings, and the ambient air temperature ranges. The data preprocessing stage included minimization of the effect of extreme fluctuations by employing the interquartile range method of outlier handling. Median substitution and linear interpolation was used to treat the missing meterological data elements. The duplicate entries were detected and removed. Thereafter, cyclic encoding was used to transform the standard weekly variable to seasonal periodicity patterns to enhance pest incidence predictions. The week numbers mentioned in the dataset were represented in terms of cosine and sine formats to ensure continuous learning of the machine learning model across cotton growing seasonal beginning and ending cycles. Furthermore, the major weather parameters of rainfall, humidity and temperature were lagged by one week so that the biologically delayed response features of pests and crop diseases could be better captured by the model.

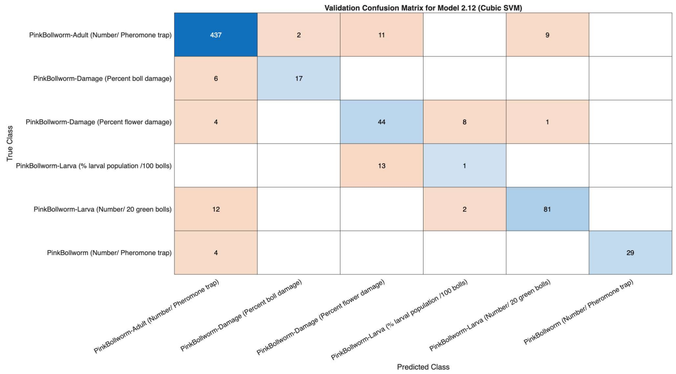
Additionally, derived predictors including Temperature Range (MaxT – MinT) and Humidity Difference (RH1 – RH2) were computed to represent diurnal microclimatic oscillations relevant to pest development. Class imbalance among pest categories was addressed using either synthetic oversampling or model-based class weighting, depending on the algorithm.

Multiple machine learning models were implemented and compared using MATLAB. Logistic Regression served as a linear baseline, while Random Forest (TreeBagger) and Gradient Boosting (fitcensemble) provided non-linear ensemble learners capable of capturing complex climatic interactions. Support Vector Machines (fitcecoc with RBF kernel) were trained for multi-class classification using one-vs-one decomposition. A shallow feedforward neural network (patternnet) was also evaluated to assess performance on non-linear tabular data. Hyperparameters for ensemble and SVM models were optimized using MATLAB's Bayesian Optimization framework to ensure fair and robust comparison. Models were trained using a stratified 80:20 split, and performance was validated using 5-fold cross-validation. Evaluation metrics included accuracy, macro- and weighted F1-scores, precision, recall, Cohen's Kappa, and multiclass confusion matrices, enabling a comprehensive assessment of both overall and class-specific performance.

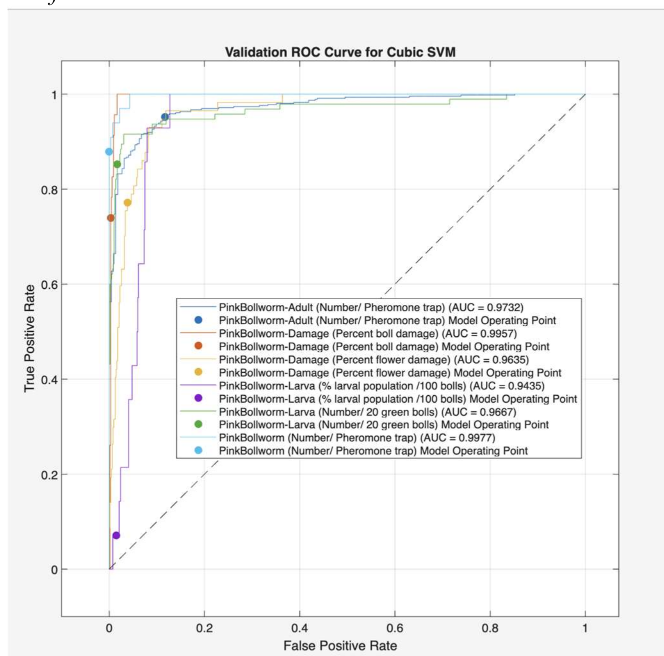
To support interpretability and agronomic relevance, model explainability was performed using permutation importance and Shapley Additive Explanations (SHAP). These methods identified the most influential climatic drivers associated with each pest/disease category and provided local explanations for individual predictions. SHAP summary plots, dependence plots, and feature ranking were generated to verify that the model captured meaningful biological relationships.

Finally, the entire workflow was integrated into an interactive MATLAB App developed using App Designer. The application allows users to upload weekly data, automatically preprocess features, train selected machine learning models, visualize performance metrics, and generate pest/disease predictions for new weather inputs. The trained model and preprocessing pipeline were exported as reusable .mat files for integration into decision-support systems or field-level advisory tools.

## 5 Results and Discussion




*Confusion Matrix Validation*




*Validation ROC Curve for Cubic SVM*

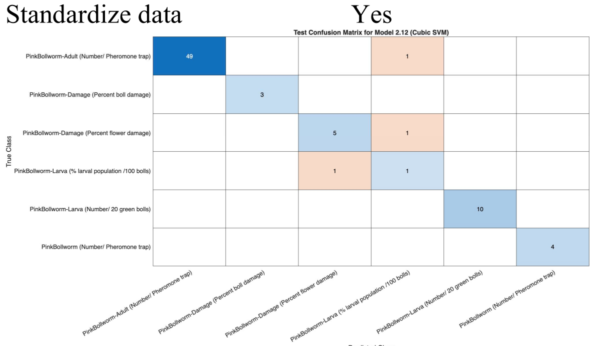
*Machine Learning - Multi-classification*

| **Model Type** | **Accuracy % (Validation)** | **Accuracy % (Test)** | **Training Time (sec)** |
|---|---|---|---|
| SVM | 89.43 | 96.00 | 150.18 |
| Neural Network | 85.17 | 96.00 | 290.10 |
| SVM | 88.84 | 93.33 | 168.60 |
| Neural Network | 88.84 | 93.33 | 291.35 |
| Neural Network | 87.08 | 92.00 | 292.07 |
| Neural Network | 87.08 | 90.67 | 292.60 |
| KNN | 86.64 | 89.33 | 271.28 |
| Efficient Linear SVM | 84.88 | 88.00 | 189.70 |

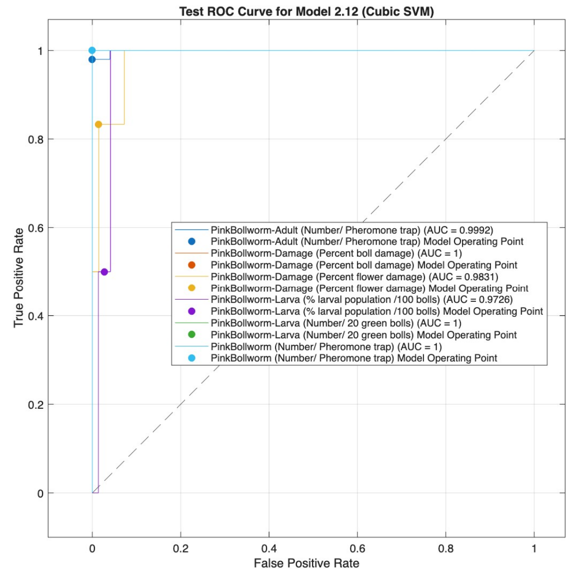
| Model Type | Accuracy % (Validation) | Accuracy % (Test) | Training Time (sec) |
|---|---|---|---|
| KNN | 85.32 | 88.00 | 252.21 |
| Ensemble | 90.75 | 88.00 | 240.58 |
| Tree | 88.84 | 86.67 | 129.10 |
| Tree | 89.57 | 86.67 | 112.13 |
| SVM | 87.67 | 86.67 | 281.01 |
| KNN | 83.70 | 86.67 | 268.81 |
| KNN | 83.26 | 86.67 | 263.49 |
| Neural Network | 86.78 | 86.67 | 288.48 |
| Efficient Logistic Regression | 84.14 | 85.33 | 197.55 |
| Ensemble | 89.57 | 85.33 | 246.34 |
| Kernel | 86.64 | 85.33 | 287.14 |
| KNN | 83.11 | 84.00 | 260.02 |
| Ensemble | 82.09 | 84.00 | 225.75 |
| Naive Bayes | 79.15 | 82.67 | 180.96 |
| SVM | 80.03 | 82.67 | 175.02 |
| Tree | 81.20 | 81.33 | 214.40 |
| Ensemble | 83.41 | 80.00 | 214.16 |
| Discriminant | 77.24 | 77.33 | 208.14 |
| Ensemble | 71.22 | 77.33 | 235.72 |
| SVM | 73.13 | 74.67 | 284.34 |
| Kernel | 76.95 | 74.67 | 285.10 |
| KNN | 70.04 | 69.33 | 266.45 |
| SVM | 68.43 | 68.00 | 274.57 |

*SVM Hyperparameter Settings - Test Accuracy-96.00%*

| Hyperparameter | Setting/Value |
|---|---|
| Preset | Cubic SVM |
| Kernel function | Cubic |
| Kernel scale | Automatic |
| Box constraint level | 1 |
| Multiclass coding | One-vs-One |
| Standardize data | Yes |




*Confusion Matrix Validation Testing*




*Testing ROC Curve for Cubic SVM*

## 6 Conclusions

This study demonstrated that machine learning models trained on weekly agro-meteorological variables can accurately classify cotton pests and diseases. Incorporating cyclic week encoding, lagged weather features, and derived climatic indicators significantly enhanced the ability of the models to capture seasonal patterns and biological responses. Ensemble learning methods, particularly gradient boosting–based approaches, provided the highest accuracy and strong robustness in handling multi-class pest/disease categories.

Explainability analysis using SHAP confirmed that minimum temperature, humidity patterns, rainfall, and sunshine hours were the most influential predictors governing pest distribution. The methodology was implemented in a MATLAB-based application, enabling easy data processing, model training, visualization, and prediction. Overall, the study presents a practical and interpretable data-driven solution for climate-informed pest surveillance that can support timely decision-making in precision agriculture.

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