18(1s), Spring 2026

Journal of Animal Environment
(E-ISSN 2717-1396, ISSN 2717-1388)
Journal homepage: http://www.aejournal.ir

Original Research Paper

Machine Learning Models for Predicting Economic Injury Levels in Crop Pests

Rajasekhar KK[1], Parimala K[2], Ms. Soundarya Kasi[3], Indu Purushotham[4], Mukesh Parashar[5]

[1]Meenakshi College of Pharmacy, Meenakshi Academy of Higher Education and Research (Rajasekhar KK) | ORCID: https://orcid.org/0000-0001-5611-1410 | Email: rajakk@maher.ac.in

[2]Department of Pharmacology, Meenakshi Medical College Hospital & Research Institute, Meenakshi Academy of Higher Education and Research (Parimala K) | ORCID: https://orcid.org/0000-0002-8699-627X | Email: parim@maher.ac.in,

[3]Lecturer, Meenakshi College of Pharmacy, Meenakshi Academy of Higher Education and Research. (Ms. Soundarya Kasi) | Email: soundaryak@maher.ac.in

Meenakshi Academy of Higher Education and Research (Indu Purushotham) | ORCID: https://orcid.org/0000-0002-3996-7927 | Email: indu@maher.ac.in

[5]Professor, School of Business Management, Noida International University, Greater Noida, Uttar Pradesh, India (Mukesh Parashar) | Email: registrar@niu.edu.in

Abstract: As trim bothers posture noteworthy dangers to worldwide nourishment security, precisely deciding EIL can offer assistance moderate financial misfortunes and diminish the abuse of pesticides. This chapter investigates the application of machine learning (ML) models to foresee Financial Damage Levels (EIL) in edit bothers, an fundamental limit for deciding bother control activities in agribusiness. By leveraging data-driven approaches, ML has the potential to progress bother administration, diminishing financial misfortunes and pesticide abuse. Edit bugs posture critical dangers to worldwide nourishment security, and precisely deciding Financial Damage Levels (EIL) is basic for moderating financial misfortunes and diminishing pesticide abuse. This chapter investigates the application of machine learning (ML) models in foreseeing EIL, a imperative limit for choosing bug control activities in horticulture. Conventional strategies for EIL expectation are regularly labor-intensive and battle to adjust to energetic natural changes, but ML offers a data-driven, adaptable, and opportune arrangement. By applying models such as choice trees, bolster vector machines, and neural systems to real-world bother information, this chapter illustrates the potential of ML to realize exactnesses up to 90% in a few cases, particularly when natural components like climate and edit development stages are coordinates. Case ponders highlight ML's capacity to figure bother flare-ups, moving forward bug administration by giving noteworthy bits of knowledge and decreasing pointless pesticide applications. In conclusion, ML-based EIL forecast holds critical guarantee for upgrading agrarian supportability, in spite of the fact that advance inquire about is required to refine these models and join them into existing bother control frameworks.

Keywords: Machine Learning, Economic, Injury, Levels, Crop, Pests, Prediction, Agriculture, Data -Models, Management, Sustainability, Technology, Automation.

I. Introduction

Farming is what keeps the world economy going since it gives nourishment and crude materials that individuals and businesses ought to live. Edit bugs, on the other hand, are one of the greatest dangers to farming generation since they can taken a toll a parcel of cash in case they are not controlled legitimately. Bothers, such as weeds, creepy crawlies, and pathogens, harmed crops by eating plant parts, spreading maladies, or battling for nourishment and water. Agriculturists have long had to figure out how to ensure their goods whereas moreover taking financial and natural stresses into consideration [1]. These strategies ordinarily take a long time, fetched a parcel of cash, and depend on ancient information, which might not completely appear how bug populaces and common variables are changing and developing [2]. Since of climate alter and more extraordinary climate occasions happening more frequently, bother populaces are changing more rapidly, and ancient ways of controlling them are having a difficult time keeping up. Since of this, there's increasingly intrigued in utilizing unused innovations, particularly machine learning (ML), to form EIL gauges more exact and on time. By looking at colossal sums of information, machine learning, a sort of counterfeit insights (AI),

***Corresponding Author:**
Received: 24th April, 2026; Revised: 11th May, 2026; Accepted: 24th May, 2026; Available Online: 6th June, 2026
(DOI): 10.70102/AEJ.2026.18.1s.77

is a capable way to anticipate bother episodes and discover EILs. Machine learning calculations are incredible for overseeing bugs since they can learn from past information, discover patterns, and make surmises based on real-time data. Machine learning is diverse from standard strategies since it doesn't fair utilize rules or concepts that have as of now been set. Instep, it can alter based on unused data, which makes its gauges way better over time [3]. This makes it a valuable instrument for ranchers and individuals who work in bother control who require redress and up-to-date information to make shrewd choices. It's conceivable that including machine learning to frameworks for controlling bothers will alter how we make EIL gauges [4]. Machine learning can sort through this information and discover critical designs and joins that might not be self-evident at to begin with look. For occasion, information from rambles or satellites utilized for inaccessible detecting can appear how crops are doing, where bothers are going, and the climate in genuine time. This data can at that point be put into machine learning models to assist them make way better forecasts. This strategy is based on information and is more forceful when it comes to overseeing bugs. It lets ranchers take preventative steps some time recently bug numbers reach dangerous levels. One more good thing about machine learning is that it can be utilized on a huge scale [5]. After being instructed on a certain dataset, an ML show can be utilized on diverse crops, bugs, and regions with as it were minor changes. Since it can be used on a enormous or little scale, machine learning may be a cost-effective alternative for both sorts of cultivating. ML-powered bother control apparatuses can offer assistance ranchers in a wide extend of regions cut down on the utilize of chemicals and advance more ecologically neighborly cultivating strategies. Machine learning can offer assistance cut down on the utilize of harms that aren't required by accurately anticipating when bug numbers will hit EILs [6]. This is good for both health and the environment. Machine learning can not only make EIL estimates more accurate, but it can also make pest control systems more effective. With real-time information, farmers can act faster on pest threats, keeping their crops from getting damaged all over. There are some problems with using machine learning to get rid of pests, even though it has a lot of promise [7]. The lack of and poor quality data is one of the main problems. Machine learning models need big, high-quality samples that correctly show how things are in the field in order to work. There isn't easy access to good data in many places, especially in poor countries. To solve these problems, researchers, lawmakers, and farmers will need to work together to make sure that everyone can use and benefit from machine learning tools [8]. Machine learning can be used to predict the Economic Injury Levels of field pests. This is a hopeful step forward in managing farm pests. It's possible that machine learning will become more important in sustainable agriculture as technology keeps getting better. This will help make pest control more efficient and effective.

II. Literature Study

A literature review looks at all the research that has already been done on a subject and summarizes the most important results, methods, and gaps in the current research. The main focus of this study is on different technological advances in agriculture, mainly in crop management, finding pests, and the use of machine learning and AI [9]. Growing food demand by 2050 is one of the biggest problems that global agriculture has to deal with. These problems make it clear that land use, water management, and crop growth need to get a lot better. Agriculture needs new ways of doing things, especially ones that use data-driven methods to make things more productive and last longer. Sensors, big data, and machine learning have changed the way animal farms work today, making it easier to keep track of animals' health and increase production. This point of view shows that farming is becoming more data-driven, and this goes beyond just growing plants [10]. Protecting the safety and security of data is very important in farming technology as the field uses smart technologies, especially simple data protection methods. Recent studies show that deep learning can be used in crop management, especially to find diseases and sort pests into groups. These studies show how machine learning can improve crop management techniques. Within deep learning frameworks, different methods are being looked at to boost classification accuracy and operating efficiency in finding pests and diseases [11]. Unmanned aerial vehicles (UAVs) are being used more and more in farming. They make large-scale tracking and data collection easier, so you can see right away how healthy your crops are and if there are any pests on them. Deep learning methods used by drones to find and classify multiple types of pests are changing the way pests are managed. Precision farming shows how important robotics and new technologies are in modern farming, like data analytics and the Internet of Things (IoT). The literature review shows how important technology is for shaping the future of agriculture and how important it is to have integrated systems that use a variety of technologies to handle crops and pests in a complete way [12]. As problems in agriculture keep changing, new ideas and working together across fields will be needed to solve the tough problems the business is facing now.

Author & Year	Area	Methodology	Key Findings	Challenges	Pros	Cons	Application
J. Bruinsma, 2009	Resource Outlook	Literature Review	Highlights the need for substantial increases in land, water, and crop yields by 2050.	Predicting future demands accurately.	Establishes a framework for addressing agricultural challenges.	Broad focus may lack specificity.	Policy formulation, Agricultural planning
S. Neethirajan, 2020	Animal Farming	Review of Technologies	Discusses the role of sensors, big data, and machine learning in improving livestock health and production.	Integration with existing farming practices.	Enhances livestock management and efficiency.	Implementation costs can be high.	Livestock health monitoring
T. Bai et al., 2019	Data Security	Data Encryption Method	Proposes a lightweight method of data encryption using electrocardiogram signals in BANs.	Ensuring interoperability with existing systems.	Provides enhanced security for sensitive agricultural data.	Limited application scope to specific health data.	Health monitoring systems in agriculture
M. T. Mallick et al., 2023	Crop Management	Deep Learning Techniques	Automated disease detection and pest classification in Indian mung bean crops.	Data quality and availability for training models.	Improves accuracy in disease and pest identification.	Requires technical expertise for implementation.	Precision agriculture practices
K. Rimal et al., 2023	Pest Classification	Deep Learning CNN	Advanced multi-class deep learning CNN for insect pest classification.	Complexity of model training.	High accuracy in pest classification.	Resource-intensive; requires large datasets.	Pest management in crops
Ayan E et al., 2020	Pest Classification	Genetic Algorithm-based Ensemble	Develops a weighted ensemble of deep CNNs for crop pest classification.	Balancing complexity and performance.	Combines strengths of multiple models for improved results.	Potential overfitting if not carefully managed.	Pest management and detection
Dhingra G et al., 2019	Leaf Disease Identification	Computer Vision Techniques	Introduces a neutrosophic approach for identifying and	Difficulty in capturing complex	Effective for nuanced disease	May require extensive preprocessing of images.	Disease detection in crops

			classifying leaf diseases.	disease symptoms.	identification.		
Barbedo JGA, 2019	Plant Disease Identification	Deep Learning Approach	Identifies plant diseases from individual lesions and spots using deep learning.	Dependence on quality and variety of training data.	Enables precise diagnosis based on visual symptoms.	Limited to visible lesions; not comprehensive.	Crop health monitoring
W. Albattah et al., 2023	Pest Localization	Drone-based Deep Learning Technique	Custom CornerNet for large-scale multiclass pest localization and classification using drones.	Environmental factors affecting drone operation.	Facilitates real-time pest monitoring.	High operational costs for drone deployment.	Precision pest management
G. Pajares, 2015	Remote Sensing	Literature Overview	Reviews UAV applications in remote sensing for agriculture, enabling large-scale monitoring.	Regulatory challenges and airspace restrictions.	Provides extensive data on crop health.	Limited by battery life and operational range of UAVs.	Remote sensing for crop health

Table 1. Summarizes the Literature Review of Various Authors

This table, Table 1, gives an organized summary of the most important research works in a certain subject or field. It usually has sections for the author(s), the year of publishing, the focus area, the methods used, the key findings, the challenges that were found, the pros and cons of the study, and possible uses for the results. Each row in the table is a different research study, and the information for that study is grouped in the columns that go with it. Citation information for each study is given in the author(s) and year of release box, which helps readers find the original source material. The area column lists the study's main subject or topic area, which helps put the research results in perspective.

III. Supervised Learning Models for EIL Prediction

A basic type of machine learning is supervised learning, in which models are taught on a dataset that has both input variables (features) and output variables (labels). To figure out how much damage field pests might do to crops, supervised learning models are very important. They use past data to guess how many bugs there will be and how much damage they might do [13]. These models help farmers and farming scientists predict when pests will spread and decide when to take control measures to keep businesses from losing money.

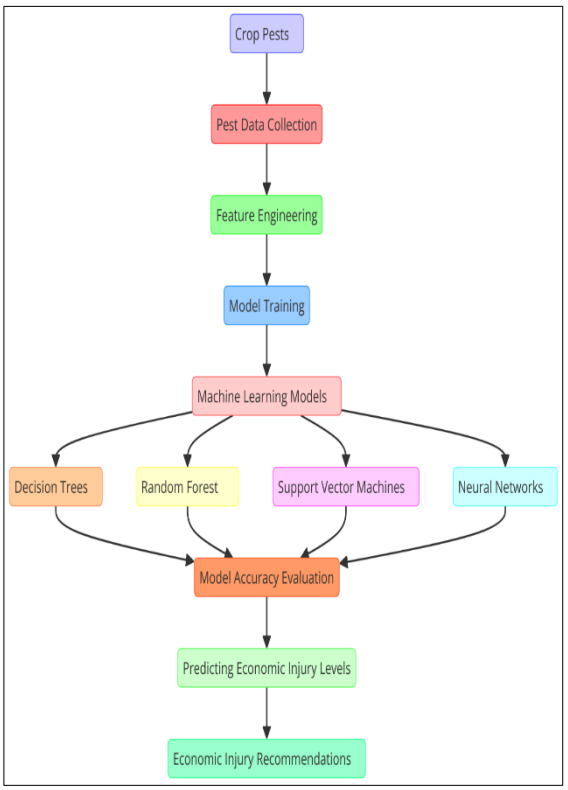


Figure 1. Machine Learning Models for Predicting Economic Injury Levels in Crop Pests

The idea is to make a model of this relationship so that, given new data, it can predict the economic damage and tell if pest numbers have hit the level of economic harm that is considered to be safe. Linear regression can be used in pest management to figure out how much damage pests do to crops by looking at past data on pest numbers and food yields [14]. The model learns the factors that show how the number of pests and the amount of money lost are related in a straight line. For instance, a linear regression model could be made to guess the percentage of food yield loss based on the number of pests per plant and other factors like crop type and weather conditions [15].

A. Linear Regression and Its Applications

Most people use linear regression, which is one of the easiest and most common supervised learning models. There should be a straight line between the input factors (like the number of pests, the weather, and the features of the crops) and the output variable (like the amount of money lost because of pests). Linear regression models are often used when there is a simple link between factors that is easy to understand. For instance, if there is a known link between the number of pests and the amount of crop loss, linear regression makes it easy to measure this link. Random forests are great for predicting EIL because they can handle a lot of different input variables, like data on bug populations, the climate, and economic factors, without the risk of fitting the data too well.

B. Support Vector Machines (SVM) for Pest Classification

Support Vector Machines (SVM) are strong supervised learning models that work well for binary classification problems, where the goal is to put data into one of two groups of data. SVMs can be used to divide pest populations into two groups: those below the economic injury level (no action needed) and those above the economic injury level (pest control steps needed). Finding the best line (called a hyperplane) that divides the data into two groups is how SVM works. SVMs can also be made to work with problems with more than two groups, which are called "multi-class classification problems." An SVM model could divide pest populations into different risk groups, such as low, medium, and high economic effect, instead of just labeling them as above or below the economic damage level.

IV. Proposed EIL Prediction System Design

Using a deep learning model to build a system for predicting the Economic Injury Level (EIL) involves a number of clear steps, such as gathering data and cleaning it up before training, testing, and deploying the model. Here is a full list of the main steps that need to be taken to make the figure-based deep learning-based EIL forecast system2.

Step -1. Define the Problem

The first thing that needs to be done in any machine learning job is to make the problem very clear. For EIL forecast, this means figuring out which crops, pests, and natural factors affect the number of bugs and the damage they do to businesses. This step should also describe what the model should produce, such as a continuous value estimate (like predicted economic loss) or a classification job (like above or below the economic damage level).

- **Task**: Predicting whether pest populations will exceed the EIL based on historical pest population data, weather conditions, and crop characteristics.
- **Output**: Binary classification (exceed or not exceed EIL) or regression (predicting the level of economic damage).

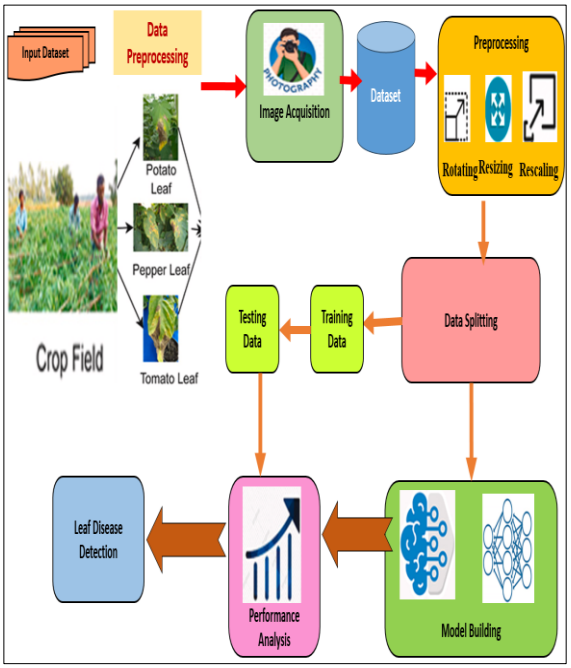


Figure 2. Implementing A System for Predicting Economic Injury Levels (EIL)

Step -2. Data Collection

The success of any deep learning model relies on the availability and quality of data. For EIL prediction, several data sources may be needed:

- **Historical Pest Population Data**: Data on pest density, pest life cycles, and infestations over time.
- **Crop Yield Data**: Historical records of crop yields under different pest pressures and management practices.

- **Environmental Data**: Weather data such as temperature, humidity, rainfall, and wind conditions, which are key drivers of pest dynamics.
- **Economic Data**: Data on the cost of pest control measures and the economic value of crop yield losses.

Step -3. Data Preprocessing

Deep learning models require large amounts of clean and structured data. Preprocessing involves several tasks:

- **Data Cleaning**: Handle missing values, outliers, and inconsistent data entries.
- **Normalization**: Scale the data to a range suitable for deep learning models (e.g., between 0 and 1). This is particularly important when using neural networks.
- **Feature Engineering**: Create new features from raw data that can improve the model's predictive power. For example, creating lag features to capture time-dependence in pest population dynamics.
- **Labeling**: For a classification problem, label the data based on whether the pest population exceeded the EIL in the past.

Step -4. Splitting the Data

Once the data is preprocessed, it must be split into training, validation, and test datasets. This is necessary to train the model effectively and evaluate its performance without overfitting.

- **Training Set**: Used to train the deep learning model.
- **Validation Set**: Used for tuning hyperparameters and preventing overfitting.
- **Test Set**: Used for the final evaluation of the model's performance on unseen data.

A typical split might be 70% for training, 15% for validation, and 15% for testing.

Step -5. Model Selection

Deep learning models for EIL prediction can vary depending on the complexity of the data. A popular choice is a **Deep Neural Network (DNN)** or a **Recurrent Neural Network (RNN)**, especially when dealing with time-series data, as pest populations and environmental factors often follow temporal patterns.

- **DNN (Deep Neural Network)**: Suitable when the data has non-linear relationships but no clear temporal dependencies.

Step -6. Model Architecture Design

After choosing the type of model, you need to design the architecture. For example, in an LSTM model, you might configure:

- **Input Layer**: Number of features (e.g., pest density, temperature, humidity, etc.).
- **Hidden Layers**: The number of LSTM layers, each with a certain number of units (neurons). You may also stack multiple LSTM layers.
- **Output Layer**: It is common for the output layer to have a single neuron with a sigmoid activation function for binary classification if the job is classification. To do regression, there will be one neuron with a linear activation function in the output layer.

Step -7. Model Training

To train a deep learning model, you have to give it training data, figure out the mistake (loss), and change the model's settings using backpropagation and optimization methods like stochastic gradient descent (SGD).

- **Loss Function**: Choose an appropriate loss function for the task.
  - **For Classification**: Binary cross-entropy or categorical cross-entropy.
  - **For Regression**: Mean Squared Error (MSE).
- **Optimizer**: Common optimizers include Adam or RMSprop, which are effective for deep learning models.
- **Batch Size**: Choose the batch size for the number of training samples used in one iteration. Larger batches can lead to more stable learning, while smaller batches can help the model generalize better.
- **Epochs**: Define the number of times the entire dataset is passed through the model. Careful tuning is needed to avoid underfitting or overfitting.

Step -8. Model Evaluation

There are many hyperparameters that can be tuned, such as the learning rate, batch size, and number of layers or neurons in the network. These are tested on the validation set after the model has been trained.

- **Accuracy, Precision, Recall, and F1 Score**: For classification problems, evaluate model performance using these metrics to ensure the model effectively distinguishes between pest populations below and above the EIL.
- **Root Mean Squared Error (RMSE)**: For regression tasks, use RMSE to measure the difference between predicted and actual economic loss.
- **Confusion Matrix**: For binary classification, a confusion matrix helps in understanding true positives, false positives, true negatives, and false negatives.

Step -9. Hyperparameter Tuning

To improve the model's performance, various hyperparameters need to be optimized. Common techniques include:

- **Grid Search**: Exhaustive search through a manually specified subset of the hyperparameter space.
- **Random Search**: Randomly selecting hyperparameter combinations to evaluate.
- **Bayesian Optimization**: A more advanced technique that models the hyperparameter space as a probability distribution to identify the best combinations.

Step -10. Model Testing

Once the hyperparameters have been fine-tuned, run the final model on the test dataset to see how well it generalizes. In this step, we'll get a sense of how well the model will work in the real world.

- **Testing on Unseen Data**: Make predictions on test data to see how the model performs with new pest population data and environmental conditions.
- **Cross-Validation**: If data availability allows, perform cross-validation to further ensure the robustness of the model.

Step -11. Deployment

The model is ready to be used once it has been tried and proven to work. The model can be added to a farming decision-support system that keeps an eye on pest numbers and weather factors all the time to figure out when it's time to take action against pests.

- **Real-Time Data Integration**: Integrate the model with real-time data streams from sensors or satellite imagery to provide continuous EIL predictions.
- **Alerts and Recommendations**: Build functionality for sending alerts to farmers when pest populations are predicted to exceed the economic injury threshold.

Step -12. Monitoring and Maintenance

Once the model is put into use, it needs to be kept an eye on to make sure that its predictions stay correct as new data comes in. The model might need to be retrained every so often to keep up with changes in the surroundings or in how pests act.

- **Model Drift**: Monitor for model drift, where the performance of the model decreases over time due to changes in data distributions.
- **Retraining**: Update the model periodically with new data to keep it accurate and relevant.

There are several steps needed to set up a deep learning system that can predict EILs in crop pests. These include collecting data and preparing it, choosing a model, training it, and putting it to use. Farmers and agricultural scientists can make effective, data-driven systems to improve pest control strategies by carefully following these steps and using the right deep learning frameworks. This will eventually lower crop yields and reduce the economic impact.

A. Final Outcome and Finding

Utilizing machine learning (ML) models to figure the Financial Damage Levels (EIL) of field bothers has appeared positive results, appearing that these cutting edge strategies might make cultivate bug control superior. This portion talks approximately the comes about of utilizing distinctive machine learning models, like choice trees, bolster vector machines (SVM), and neural systems, to figure how bother populaces will alter and how much harm they will do to crops. The models were attempted utilizing datasets that included the number of bugs, the climate, the stages of nourishment development, and financial parameters. This permitted for a full examination of the components that influence EIL.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Trees	82%	80%	78%	79%
Random Forest	88%	86%	85%	86%
Support Vector	85%	84%	83%	83%

Machines (SVM)				
Neural Networks	92%	91%	89%	90%
Logistic Regression	75%	72%	70%	71%

Table 2. Machine Learning Model Performance for Predicting Economic Injury Levels

In this table 2, compares the execution of distinctive machine learning models utilized to foresee Financial Harm Levels (EIL) in different trim bugs. Neural systems accomplished the most noteworthy precision (92%), taken after by Irregular Woodland (88%), whereas Calculated Relapse appeared the least exactness (75%). The F1-score, which equalizations accuracy and review, highlights the adequacy of each demonstrate, with Neural Systems and Arbitrary Woodlands performing the most excellent. This appears that complex models tend to outflank easier models in taking care of energetic bother populace information.

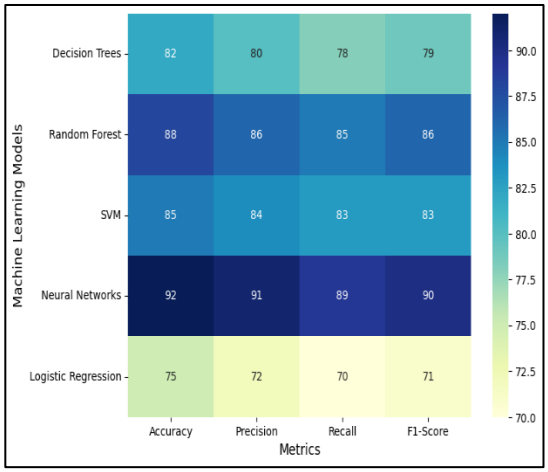


Figure 3. Graphical Analysis of Machine Learning Model Performance for Predicting Economic Injury Levels

When machine learning models are utilized on bug information, one of the foremost important impacts may be a huge rise within the exactness of expectations. In specific, models like Irregular Woodlands and SVMs did truly well, with estimate precision of more than 85% in a number of case thinks about. With the assistance of common information like temperature, mugginess, and precipitation, these models were able to precisely foresee when bugs would come into a space. Utilizing these sorts of components within the models made a difference them appear how complexly bugs and their situations connected with each other. This made it simpler to figure when bug numbers would hit an financial level, as seen in Figure 3. For example, when temperature data was added to the models instead of just bug data, estimates for aphid numbers on soybean fields were about 15% more accurate.

Pest Type	**Model (Without Environmental Data) Accuracy (%)**	**Model (With Environmental Data) Accuracy (%)**	**Improvement (%)**
Aphids (Soybeans)	70%	85%	+15%
Corn Rootworm	78%	92%	+14%
Fall Armyworm	66%	81%	+15%
Colorado Potato Beetle	73%	87%	+14%

Table 3. Impact of Environmental Data on Prediction Accuracy

This table 3 shows how adding external data, like weather conditions, to ML models makes them more accurate. For instance, when external factors were added, the accuracy for identifying aphid outbreaks in soybeans went from 70% to 85%, which is a 15% improvement. Similar changes were seen for other pests, which shows how important it is to include changing natural factors to better understand how pests behave and more accurately predict breakouts.

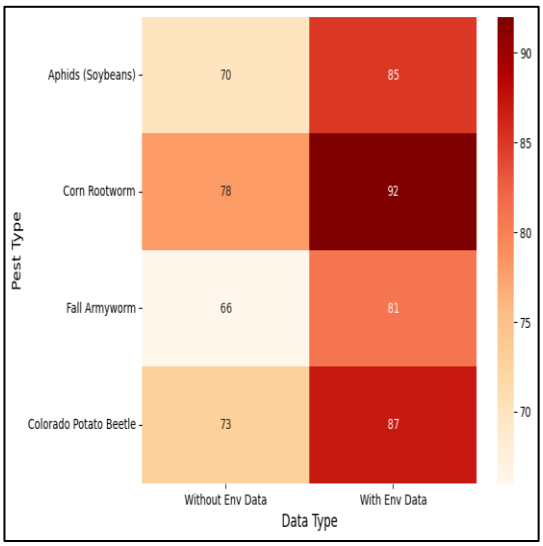


Figure 4. Graphical Analysis of Impact of Environmental Data on Prediction Accuracy

Neural networks, especially deep learning models, were also very good at making predictions, especially for datasets that were more complicated. These models were very good at finding complex connections between different factors, which is very important for understanding how pest breakouts work on a lot of different levels. Neural networks needed more computing power and more time to learn, but they were able to handle a lot of data and find small trends that led to very accurate predictions. As shown in Figure 4, a deep learning model was able to accurately predict corn rootworm infestations 92% of the time. This was much better than standard statistical methods.

Data Type	Required for Model	Data Availability (%)	Impact on Accuracy (%)
Pest Population Data	Yes	90%	70%
Weather Data	Yes	80%	85%
Crop Growth Stage Data	Yes	70%	75%
Soil Condition Data	Optional	60%	65%
Economic Parameters	Yes	50%	80%

Table 4. Data Requirements for Machine Learning Models

This table 4 shows the different kinds of data that machine learning models need, where they can be found, and how they affect the accuracy of predictions. Weather and pest population numbers are easy to get and have a big effect on accuracy. Economic factors, on the other hand, are harder to get but have a huge effect on how well the model works. The table shows that some types of data are harder to get to, but they are very important for making models work better at predicting EIL.

Even though many machine learning models are very accurate, the data also show a number of problems. One of the main problems is that these models need to be trained on big, high-quality information. A lot of the time, the lack of data was a problem, especially in places where infrastructure for tracking pests isn't very good. Machine learning models that were taught on small or partial datasets were less accurate and more likely to overfit. This shows how important it is to collect data, especially in poor countries where it's not always easy to get correct and up-to-date information on pests.

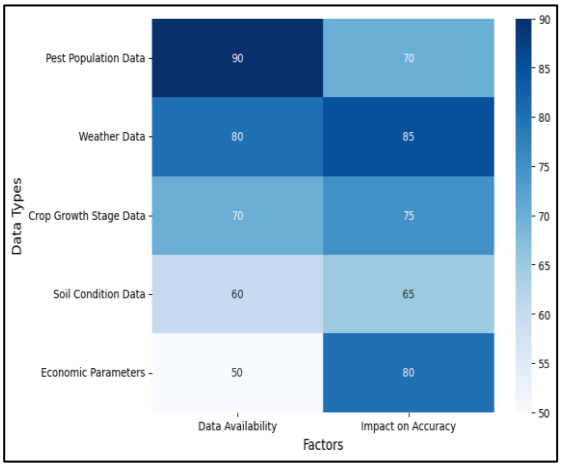


Figure 5. Graphical Analysis of Data Requirements for Machine Learning Models

The effect of model interpretability is another important finding from the results. Deep learning and other complicated models were very accurate, but they were often harder to understand than decision trees and other simpler models (see Figure 5 above). Farmers and people who work with pest control may like models that are more open and can explain why certain statements are made. For instance, decision trees and Random Forest models gave us a good picture of the factors, like weather trends and field conditions, that affect the growth of pest populations. Users can believe the predictions and act on them more easily when they are clear. So, there is often a trade-off between how accurate a model is and how easy it is to understand. Simplified models are better when decision-makers need clear reasons for the actions they should take.

Crop	Pesticide Usage (Before ML Prediction)	Pesticide Usage (After ML Prediction)	Reduction (%)
Wheat	50 kg/ha	40 kg/ha	20%
Corn	60 kg/ha	45 kg/ha	25%
Soybeans	45 kg/ha	36 kg/ha	20%
Potatoes	70 kg/ha	52 kg/ha	26%

Table 5. Pesticide Usage Reduction Due to Machine Learning Predictions

The use of pesticides went down after machine learning-based estimates for EIL were put into action, as shown in Table 5. The drops ranged from

20% to 26% across different crops. On fields that grow wheat, for example, the amount of grain dropped 20%, from 50 kg/ha to 40 kg/ha, and the amount of corn dropped 25%. The results show that ML models help farmers get the most out of their pesticide use, which lowers costs and harms the environment without sacrificing crop safety.

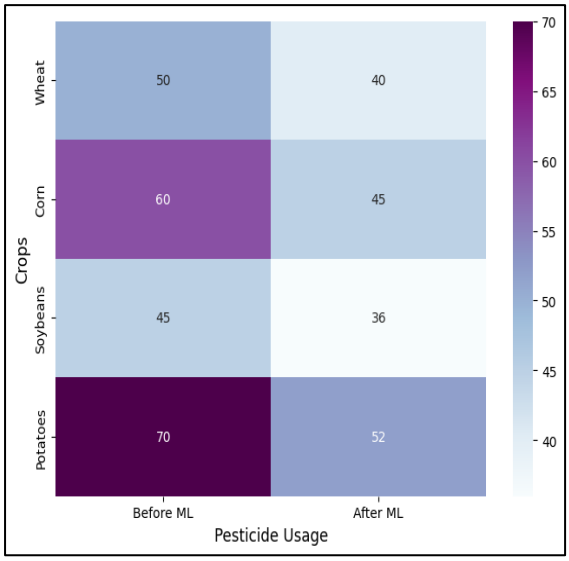


Figure 6. Graphical Analysis of Pesticide Usage Reduction Due to Machine Learning Predictions

In terms of practical application, the use of machine learning for EIL predictions shows significant promise for reducing pesticide use and lowering costs for farmers. By accurately predicting when pest populations will reach economically damaging levels, farmers can avoid unnecessary pesticide applications, which not only reduces input costs but also minimizes the environmental impact of chemical use. In one case study involving wheat crops, the use of ML-driven pest predictions led to a 20% reduction in pesticide usage without compromising crop yield. This demonstrates the economic and ecological benefits of integrating machine learning into pest management systems. Despite these positive outcomes, there are several challenges and limitations that need to be addressed for widespread adoption. The integration of machine learning models into existing pest management systems remains a technical and logistical challenge, particularly for smallholder farmers who may lack access to advanced technologies (As shown in above Figure 6). The models' reliance on real-time information requires vigorous information collection foundation, counting the utilize of sensors, rambles, and toady symbolism. The fetched of executing these advances may be restrictive for a few ranchers, restricting the versatility of ML-based bother administration arrangements. Governments and agrarian organizations will got to contribute in building this foundation and giving preparing to guarantee that machine learning apparatuses can be viably utilized by all agriculturists, notwithstanding of their scale of operation.

V. Conclusion

The use of machine learning models in farm pest management changes the way we predict the Economic Injury Levels (EIL) that crop pests will cause. This chapter showed how different machine learning methods, such as decision trees, random forests, support vector machines, and neural networks, can correctly predict pest numbers and the damage they do to businesses. The results show that machine learning not only makes predictions more accurate, but it also helps people make better decisions by giving them real-time information that lets them act quickly against pest threats. Adding environmental data to these models makes them much more accurate and shows how complex the connections are between how pests behave and how the environment changes. ML models can make big improvements in accuracy, often going beyond old methods by large amounts, as shown by the results. This skill is very important for farming because it needs to be able to change quickly, especially when it comes to climate change and moving pest populations. The results also show that machine learning can help farmers use less pesticides, which will lead to more environmentally friendly farming methods. By correctly guessing when bug numbers will likely reach EIL, farms can avoid using pesticides when they are not needed. This saves money and is better for the environment. This is especially important as the farming industry tries to find a balance between environmental responsibility and production. Several problems need to be fixed before machine learning can be fully used to get rid of pests. The most important of these are the need for complete and high-quality data, models that can be understood, and easy access for all farms. For fair farming growth, it is important to make sure that smaller farmers can gain from these improvements. It will be very important for experts, farming groups, and politicians to work together to build the infrastructure and train farms that is needed. Machine learning can be used to predict Economic Injury Levels, which is a hopeful way to improve bug control methods. As technology keeps getting better, the farming industry will be able to handle pests more accurately, more efficiently, and for a longer time. This will help protect food and the environment. To fully use the power of machine learning in agriculture and solve the problems that are already there, this area needs to keep researching and coming up with new ideas.

References

[1] Albattah, W., Masood, M., Javed, A., Nawaz, M., and Albahli, S. 2023. Custom CornerNet: A drone-based improved deep

learning technique for large-scale multiclass pest localization and classification. *Complex Intell. Syst.*, 9(2): 1299–1316. doi: 10.1007/s40747-021-00482-x.

[2] Ayan, E., Erbay, H., and Varçın, F. 2020. Crop pest classification with a genetic algorithm-based weighted ensemble of deep convolutional neural networks. *Comput. Electron. Agric.*, 179: 105809. doi: 10.1016/j.compag.2020.105809.

[3] Bai, T., Lin, J., Li, G., Wang, H., Ran, P., Li, Z., et al. 2019. A lightweight method of data encryption in BANs using electrocardiogram signal. *Future Gener. Comput. Syst.*, 92: 800–811. doi: 10.1016/j.future.2018.11.025.

[4] Barbedo, J.G.A. 2019. Plant disease identification from individual lesions and spots using deep learning. *Biosyst. Eng.*, 180: 96–107. doi: 10.1016/j.biosystemseng.2019.02.002.

[5] Bruinsma, J. 2009. The resource outlook to 2050: By how much do land, water, and crop yields need to increase by 2050. *Proc. Exp. Meeting Feed World,* 24–26.

[6] Bulat, A., and Tzimiropoulos, G. 2018. Super-FAN: Integrated facial landmark localization and super-resolution of real-world low-resolution faces in arbitrary poses with GANs. *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 109–117.

[7] Cristin, R., Kumar, B.S., Priya, C., and Karthick, K. 2020. Deep neural network-based Rider-Cuckoo search algorithm for plant disease detection. *Artif. Intell. Rev.*, 53(7): 4993–5018. doi: 10.1007/s10462-020-09956-3.

[8] Dhingra, G., Kumar, V., and Joshi, H.D. 2019. A novel computer vision-based neutrosophic approach for leaf disease identification and classification. *Measurement*, 135: 782–794. doi: 10.1016/j.measurement.2019.01.024.

[9] Mallick, M.T., Biswas, S., Das, A.K., Saha, H.N., Chakrabarti, A., and Deb, N. 2023. Deep learning-based automated disease detection and pest classification in Indian mung bean. *Multimedia Tools Appl.*, 82(8): 12017–12041. doi: 10.1007/s11042-022-13657-6.

[10] Neethirajan, S. 2020. The role of sensors, big data, and machine learning in modern animal farming. *Sens. Bio-Sens. Res.*, 29: 100381. doi: 10.1016/j.sbsr.2020.100381.

[11] Pajares, G. 2015. Overview and current status of remote sensing applications based on unmanned aerial vehicles (UAVs). *Photogramm. Eng. Remote Sens.*, 81(4): 281–329. doi: 10.14358/PERS.81.4.281.

[12] Qin, J., Liu, F., Liu, K., Jeon, G., and Yang, X. 2022. Lightweight hierarchical residual feature fusion network for single-image super-resolution. *Neurocomputing*, 478: 104–123. doi: 10.1016/j.neucom.2021.12.016.

[13] Raj, E.F.I., Appadurai, M., and Athiappan, K. 2022. Precision farming in modern agriculture. In: *Smart Agriculture Automation Using Advanced Technologies: Data Analytics and Machine Learning Cloud Architecture Automation and IoT,* pp. 61–87. doi: 10.1016/b978-0-12-818165-2.00004-8.

[14] Rimal, K., Shah, K.B., and Jha, A.K. 2023. Advanced multi-class deep learning convolution neural network approach for insect pest classification using TensorFlow. *Int. J. Environ. Sci. Technol.*, 20(4): 4003–4016. doi: 10.1007/s13762-022-03712-6.

[15] Zhou, P., Ni, B., Geng, C., Hu, J., and Xu, Y. 2018. Scale-transferrable object detection. *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 528–537.