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# Autonomous Pest Detection System using IoT Sensors and Predictive Analysis using Deep Learning and GenAI Techniques

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**ABSTRACT**

To develop an autonomous smart pest detection system, the utilization of Smart IoT devices and adoption of deep learning techniques along with generative artificial intelligence techniques is necessary. Specifically designed for farming applications, the proposed system inbuilds an array of sensors comprising of an Infrared Sensor for nocturnal insect movement observation, an acoustic sensor for capturing sounds generated by the pests and environmental sensors like temperature, humidity, and light sensors, image sensors as well. The temperature sensor signifies its role in identifying optimal breeding conditions for pests prevalent in agricultural settings. The humidity sensor measures the moisture levels as per the pest activity and breeding. The light sensor monitors quantifies the pest behavior during different times of the day. These sensors are fabricated managing the pest ecosystem in farming. By using the widely adaptive deep learning techniques, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM), the collected data is trained on the smart system for precise pest identification. The use of GenAI technique, further enhances the system by introducing a Chabot capable of interpreting observed data and supporting the potential pest-related trends according to the dynamic environmental conditions. Several test cases are performed on the proposed detection system, providing the fabricated smart system as an efficient one. The results and performance of the proposed system is well-suited for deployment in agricultural settings, with the potential that improves both the quality and quantity of crops in farming practices

**Keywords:** *Smart Agriculture, Pest Detection, IoT Sensors, Deep Learning Techniques, Generative AI Chatbot*

## 1. INTRODUCTION

Insect monitoring plays a vital role to preserve biodiversity, sustainably cultivate crops and mitigate vectors of diseases having direct impact on humans and livestock. The traditional methods of insect trapping and identification seems to be a time-consuming process with high costs. In case of ignoring the pest detection, there may arise of scenarios with several diseases. Hence, controlling and effectively managing insect populations is significant to the farmers in maintaining the health their crops.

From the recent studies, it is being understood the demand for IoT-based smart system in the agricultural sector. This signifies the need for an autonomous technique that efficiently detects the pests and performs the predictive analysis on pests.

The smart IoT-based device incorporates predictive maintenance by embedding the deep learning model and GenAI technique. The IoT sensors captures the pest details and transfers the captured data to the deep learning model for further processing and even to perform the predictive analysis.

Moreover, the smart system comprising of IoT sensors can be used to collect the dynamic features of the pests in the real-time agriculture lands.

The deep learning techniques, especially the Convolutional Neural Networks is trained with visual data captured from smart IoT devices that are installed the agricultural or farm lands.

The Recurrent Neural Network model with LSTM architecture focuses on temporal features that are dynamic in nature of the pests and retains contextual information pertaining to the pest behavior.

Furthermore, the utilization of GenAI tools provides the independence and adaptive system. The Generative Adversarial Networks (GANs) supports in creation of synthetic data with several pest scenarios. This synthetic data is augmented to add efficiency to the training process by addressing the diverse pest-related challenges. Additionally, realistic pest scenarios ensures the robustness of the autonomous and smart pest detection system.

The implementation of CNNs, RNNs with LSTM and GenAI tools as a smart IoT device makes the farmers to work with an autonomous pest management device. This real-time product handles pest dynamics providing fast and dynamic responses to get enhanced crop yields. This smart pest detection strategy enforces sustainable agriculture.

The significant areas incorporated in the proposed system are:

1. **Design and Implementation of an IoT-Based Pest Detection Model:**
   - A smart circuit with IoT sensors is designed and developed for pest detection in agricultural lands to enhance the quality and quantity of yields.
2. **Integration of Advanced Deep Learning Architecture:**
   - The proposed work implements the deep learning architecture, Convolutional Neural Networks (CNN). This system extracts most important features from images using YOLOv3 model. The extracted features are then classified using optimized parameters to improve accuracy.
3. **Utilization of Recurrent Neural Network with LSTM:**
   - To optimize the analysis of time-series data collected from IoT-connected sensors, the Long Short-Term Memory (LSTM)-based Recurrent Neural Network (RNN) is implemented in the smart system. This application enhances the performance of the model in handling sequential data pertinent to pest detection.
4. **Application of Generative Artificial Intelligence:**
   - The article employs generative artificial intelligence techniques to predict information related to pest detection based on environmental factors. This innovative approach aids in providing insightful predictions regarding pest presence and behavior.

This flow of the paper includes: The second section offers an extensive background review encompassing various pest detection strategies. In Section 3, we delineate the methodologies developed in conjunction with the technologies employed for analyzing data sourced from smart IoT devices specifically utilized for pest detection. Then, Section 4 presents the prime findings and summarizes the obtained results. Finally, Section 5 provides the conclusion comprising of future research and scope

## 2. THEORETICAL BACKGROUND

Smart devices comprising of IoT sensors plays a vital role in farming. Especially to have a mention, the IoT-based agriculture framework by (Gao et al., 2020) ensures data acquisition and visualization encompassing data associated with pests and environmental conditions that seems to be dynamic. Similarly, it is also highlighted by (Farooq et al., 2020) that provides smart devices that ensures the quality of crop (Azfar et al., 2018). The acoustic technique (Mankin et al., 2011) used for specific sound-generating pests has limited scope.

Commercial pest management systems enable farmers to remotely monitor and assess pest activity within their fields (Gaikwad et al., 2021). Additionally, the incorporation of passive infrared (PIR) sensing technology in pest traps facilitates the identification of target pests by analyzing emitted heat levels.

The acoustic sound plays a vital role in prediction of type of pests (Warren et al., 2009) as it varies according to its location. The wingbeat frequency of the pests (Clements, 1999) produces the audibility in harmonics. Basically, digital signal theory is applied for audio feature extraction (Humphrey et al., 2013) and presented an efficient feature representation suitable for pest detection.

The application of Artificial Intelligence (AI) techniques for pest prediction proves advantageous for farmers, minimizing pesticide usage (Magarey, 2015). Predictive analysis on pest threats ensures pest control and reducing crop losses.

The Wi-Fi-connected image monitoring system (Rustia et al., 2017) utilized traps equipped with sensors and cameras positioned at an 80 mm distance. Captured images were transmitted to a remote server every 10 minutes for processing, enabling effective pest detection.

The challenging task associated with publicly available datasets (Li et al., 2021) associated with deep learning model is labeling.

There exist two limitations while using Convolutional Neural Network (CNN)-based pest detection. The first and the foremost limitation is the size and density distribution of pests as these two factors influence the training of the system (Ana Sanz-Aguilar et al., 2020). The next limitation is the data quantity imbalance in terms of pest types.

The Long Short-Term Memory (LSTM) along with Recurrent Neural Network (RNN) is widely used for (Chen et al., 2020) pest identification in farm lands.

The combined technologies such as IoT, deep learning and GenAI in agriculture represents a positive hope in the national economy. And these cutting-edge technologies ensure the efficiency in pest detection and management.

## 3. DATA AND METHODS

This proposed smart system works on several datasets. More significantly the IP102 is associated with agricultural pest detection. The IP102 dataset comprises of 75,000 images with nearly 102 types of pests. The dataset exhibits real-world prevalence of insect pests. And 19,000 images are annotated related to pests. The dataset features focus on specific agricultural products. It also provides the relationships between different pest species and their respective host crops, offering significant information for agricultural research and pest management strategies. Figure 1.1 shows the sample images from IP102 dataset.

Table 1.1 shows the images of pests on Datasets.

**Table 1.1 Category of species of pests**

| ID | Insect | Categories | Images per Taxa |
|---|---|---|---|
| D1 | Flies | 11 Families | 24 – 159 |
| D2 | Beetles | 14 Families | 18 - 900 |
| D3 | Beetles | 3 Species | 40 – 205 |
| D4 | Stone Flies | 9 Species | 107 - 505 |

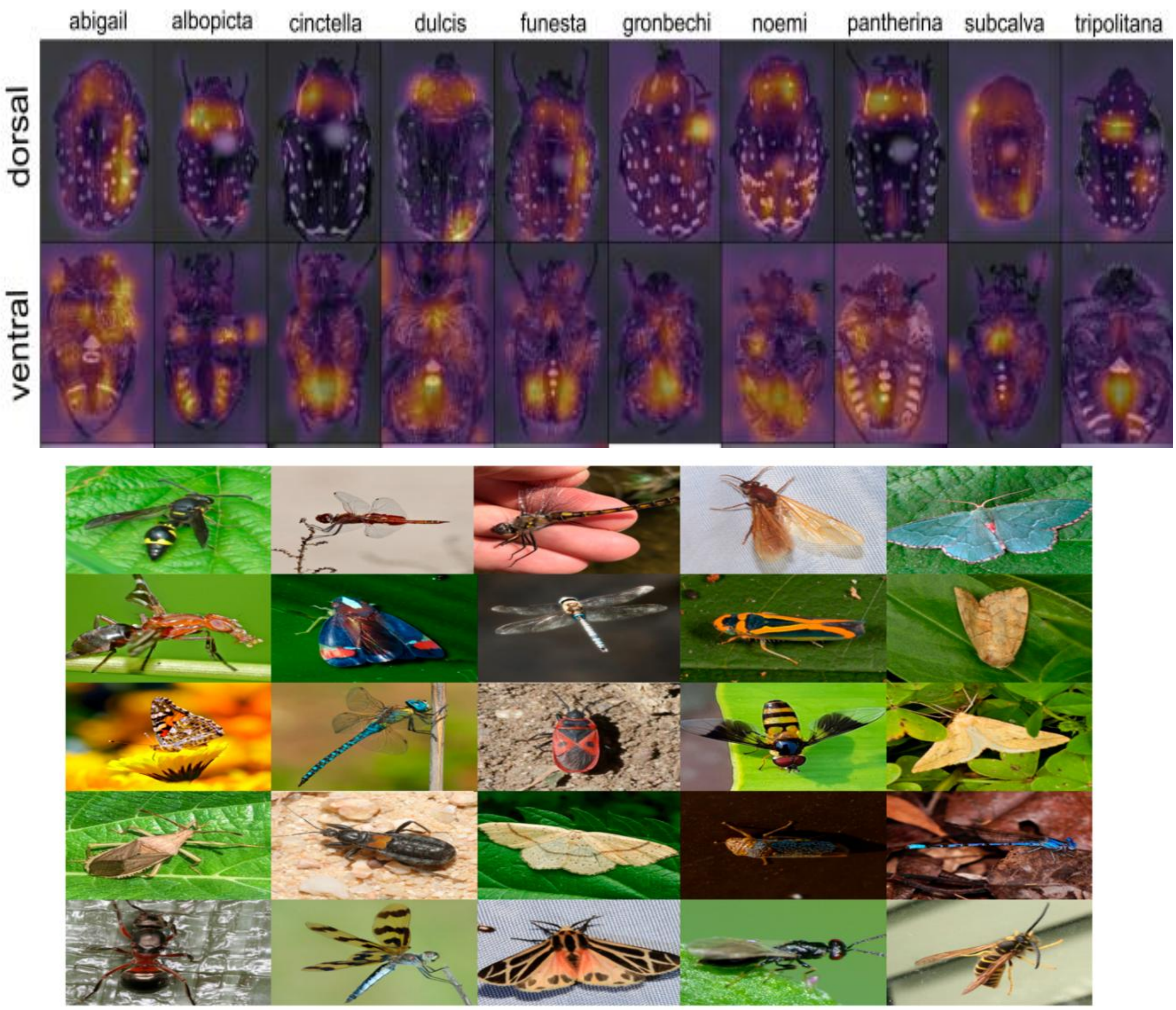
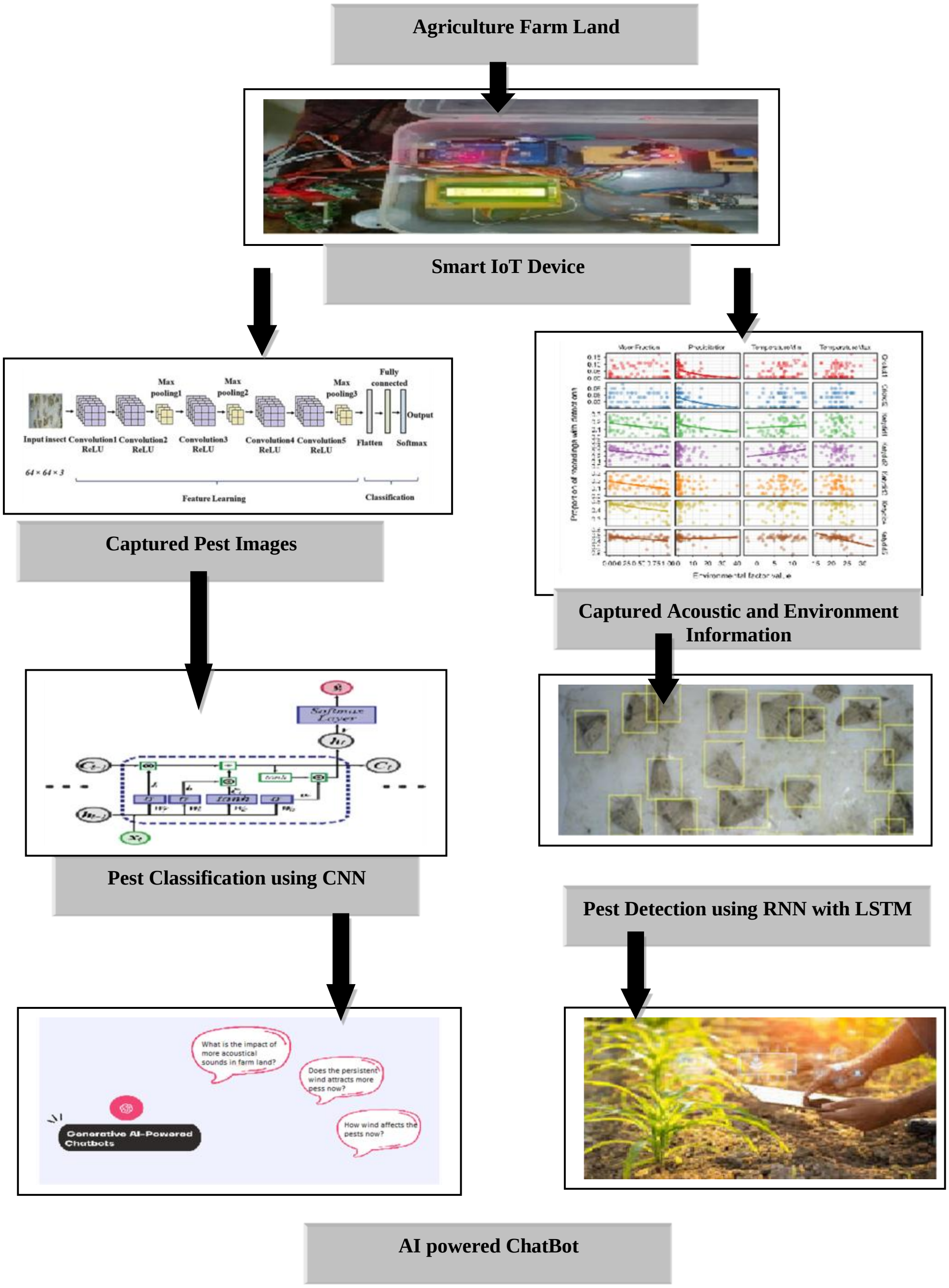



**Figure 1.1 Sample Pest Images from IP102 Dataset**

The below shown figure (Figure 1.2) shows the architecture of IoT based smart agriculture farming in detecting pests and find whether the prevailing environmental conditions is suitable for farming.

**Figure 1.2 Architecture of Smart IoT based Agriculture Farming for detecting Pests**




The architecture shows that the smart IoT device is built with Infrared sensors, Ultrasonic sensors, Image sensors, and environmental sensors such as temperature, humidity, and light sensors. The smart device generates the data continuously. The generated data is used for detection of pests in the farm. The convolutional neural network uses IP102 dataset to detect and recognize the pests.

(i) Input Layer

The Input layer represents the raw image data. In the context of the IP102 dataset, each image would be fed into the network. Let X represents the input image.

(ii) Convolutional Layer

Convolutional layers extract significant features. Let F represent the filter, and ∗ denote the convolution operation. This layer produces.

$$H = F * X \qquad (1.1)$$

(iii) Activation Function (ReLU)

To introduce non-linearity ReLU is used as:

$$H_{\text{activated}}=\text{ReLU}(H) \qquad (1.2)$$

(iv) Pooling Layers

The spatial dimensions are reduced as :

$$\text{H}_{\text{pooled}}=\text{P}(\text{H}_{\text{activated}})H_{\text{pooled}}=P(H_{\text{activated}}) \qquad (1.3)$$

(v) Flattening Layer

This results in 1D vector.

(vi) Fully Connected Layers

This layer provides the output as,

$$\text{O}=\text{W}\cdot\text{flatten}(\text{H}_{\text{pooled}})+\text{b} \qquad (1.4)$$

(vii) Output Layer

Softmax activation is used in this layer.

This architecture is then trained using the IP102 dataset.

The algorithm for detection of pest is shown below:

**Algorithm : Pest Detection on spectral features**

For each feature do

For each class in Ci do

Collect maximum N predictions, $y_i$

Collect corresponding inputs, $X_i$

Forming a concatenation of 2D images with dimensions h1 × w1

Collect $N_s$ training samples and frame $X_{i,\text{ train}}$

Take average across patches and individual columns:

$$x_{i,test}(f)\frac{1}{w1}\frac{1}{N}\sum_{j=1}^{w1}\sum_{k=1}^{N}X_{ijk,test}$$

$$x_{i,train}(f)\frac{1}{w1}\frac{1}{N}\sum_{j=1}^{w1}\sum_{k=1}^{N}X_{ijk,train}$$

Normalise by mean and standard deviation

end for

end for

**The implementation of CNN for pest classification includes hyperparameters and several epochs as shown below:**

| CNN Layers | Output Shape | Parameters |
| --- | --- | --- |
| First Conv layer | (272, 363, 64) | 1792 |
| Second | ( 272, 363, 64) | 36928 |
| Pooling | (136, 181, 64) | 0 |
| Conv layer | (136, 181, 128) | 73856 |
| Max Pooling | (68, 90, 128) | 0 |
| Conv | (68, 90, 256) | 295168 |
| Max Pooling | (34, 45, 256) | 0 |
| Conv | (34, 45, 512) | 1180160 |
| Max Pooling | (17, 22, 512) | 0 |
| Conv | (17, 22, 512) | 2359808 |
| Max Pooling | (8, 11, 512) | 0 |
| Flatten | (45056) | 0 |
| Dense | (1024) | 46138368 |
| Dense 1 | (1024) | 1049600 |
| Dense 2 | ( 25) | 25625 |
| Total parameters: 51,161,305 | | |
| Trainable parameters: 51,161,305 | | |
| Non-trainable parameters: 0 | | |

The hyperparameters used in the CNN model is shown in Table 1.2

**Table 1.2 Hyperparameters of CNN Model**

| Hyperparameter | Value |
| --- | --- |
| Optimizer | Adam |
| Momentum | 0.98 |
| Epochs | 60 |
| Batch Size | 32 |
| Drop out Rate | 0.5 |
| No. of Layers | 9 |
| Learning Rate | 0.01 |
| Loss Function | Cross Entropy |

The RNN uses the acoustic information from the smart IoT device to identify the pests.

(i) Input Layer

Let $X_t$ represent the acoustic features collected at time $t$.

(ii) LSTM Cell

The LSTM cell addresses the vanishing gradient problem.

The hidden state ($h_t$) and cell state ($c_t$) at time $t$ are updated using the following equations:

$$i_t = \sigma(W_{ii} X_t + b_{ii} + W_{hi} h_{t-1} + b_{hi}) \quad (1.5)$$

$$f_t = \sigma(W_{if} X_t + b_{if} + W_{hf} h_{t-1} + b_{hf}) \quad (1.6)$$

$$o_t = \sigma(W_{io} X_t + b_{io} + W_{ho} h_{t-1} + b_{ho}) \quad (1.7)$$

$$g_t = \tanh(W_{ig} X_t + b_{ig} + W_{hg} h_{t-1} + b_{hg}) \quad (1.8)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \quad (1.9)$$

$$h_t = o_t \odot \tanh(c_t) \quad (1.10)$$

Here, $\sigma$ represents the sigmoid activation function, $\odot$ denotes element-wise multiplication, and $W$ and $b$ are weight matrices and biases, respectively.

(iii) Output Layer

The output $Y_t$ at each time step is :

$$Y_t = \mathrm{softmax}(W_{out} h_t + b_{out}) \quad (1.11)$$

(iv) Loss Function

The categorical cross-entropy is used as a loss function.

(v) Training

The weights and biases are updated using Adam algorithm to minimize the loss function.

The GenAI technique is used to create a chatbot:

(i) Data collection and preprocessing

Collected data is again trained with generative AI model.

(ii) Model Training

Large language model (LLM), Llama is used for training.

(iii) Fine Tuning the Model

The model gets fine-tuned with the contexts associated with pest features.

(iv) Natural Language Processing

The Llama model understands the context and prompts related to pests and agricultural conditions and provides the effective answers.

(v) Predictive Analysis

Using the chatbot a predictive analysis can be done. Users can inquire about potential pest outbreaks, optimal planting times, or recommended preventive measures based on the historical and real-time data available from the IoT devices placed on agriculture farms.

## 4. EXPERIMENTAL SETTINGS AND EVALUATION

The results show that the detection performance of pests is improved when the fusion of CNN and RNN with LSTM is done. The average accuracy obtained in pest detection using IP102 is shown in Figure 1.3.

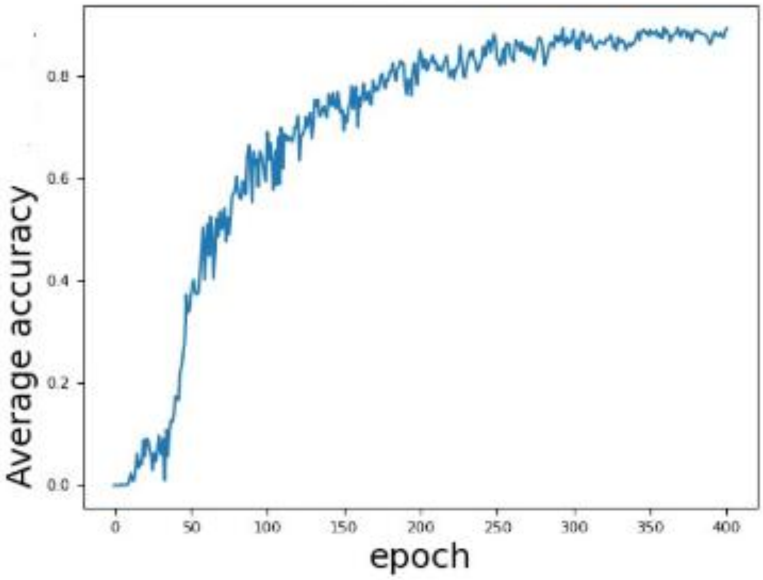


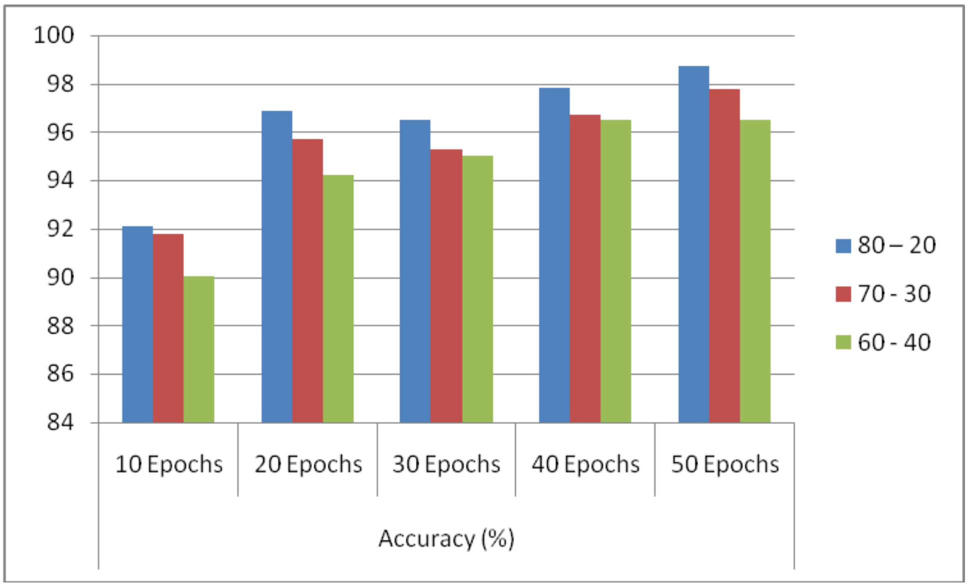

**Figure 1.3 Performance in terms of accuracy in detection of pests on IP102 dataset**

The dataset split and accuracy attained using the above dataset by the CNN classifier is shown in table 1.3.

**Table 1.3 Dataset Split on IP102 dataset**

| Dataset split (Train/Test) % | Accuracy (%) | | | | |
|---|---|---|---|---|---|
| | 10 Epochs | 20 Epochs | 30 Epochs | 40 Epochs | 50 Epochs |
| 80 – 20 | 92.11 | 96.85 | 96.5 | 97.85 | 98.75 |
| 70 - 30 | 91.78 | 95.7 | 95.3 | 96.7 | 97.75 |
| 60 - 40 | 90.04 | 94.2 | 95.01 | 96.50 | 96.50 |

The above analysis is depicted in a graph as shown in Figure 1.4. The dataset split of 80-20 % is sufficient for efficient learning and avoids overfitting. The testing and training data is selected in such a way that has direct impact over the model performance. Figure 1.4 Dataset split and its corresponding accuracy.



The wingbeat frequency of several insects observed is listed in Table 1.4 along with its effect of environmental factors. It varies according to the environmental factors like temperature, humidity, pressure etc. The acoustic activity density is shown as in Figure 1.5.

**Table 1.4 Frequency Range of Pests**

| **Pests** | **Wingbeat Frequency Range** | **Environmental Factors** | | |
|---|---|---|---|---|
| | | **Temperature** | **Humidity** | **Pressure** |
| Cricket | 3 to 6 hertz | Wingbeat frequency increases with high temperature and decreases as temperature decreases | Wingbeat frequency increases with high humidity and decreases with low humidity | Wingbeat frequency increases with high pressure and decreases with low pressure |
| Katydids | 4 to 8 hertz | | | |
| **Aedes aegypti** | 400 to 600 hertz | | | |
| **Aedes albopictus** | 400 to 600 hertz | | | |
| **Anopheles subpictus** | 450 to 550 hertz | | | |
| **Anopheles gambiae** | 400 to 600 hertz | | | |

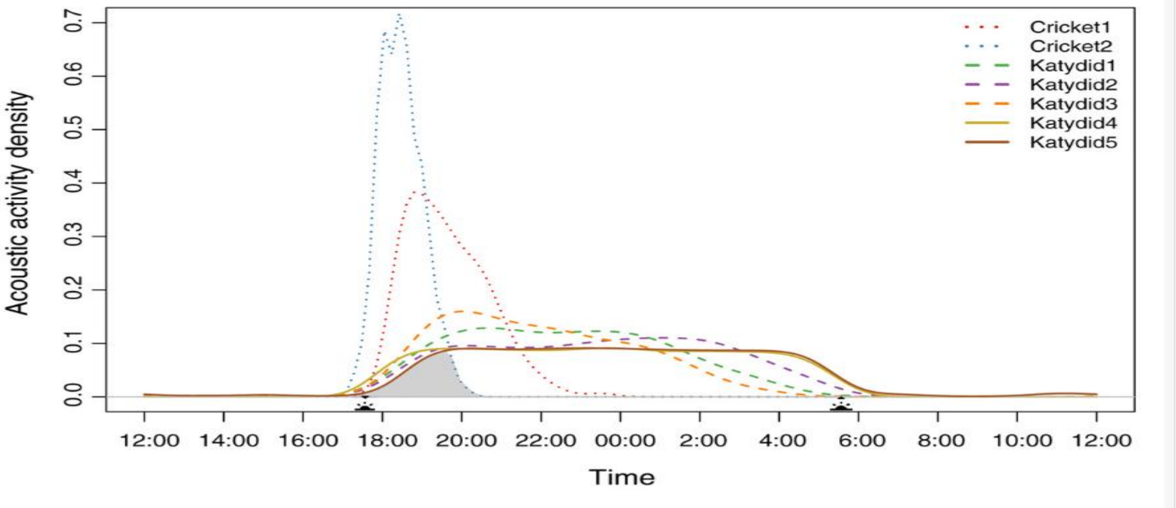



**Figure 1.5 Acoustic activity density per 2 hrs in an Agriculture Farm**

The distribution was computed based on the frequency of detections recorded every half-hour interval over the periodical course. The acoustic activity density also signifies the result. The shaded region shows that of a dusk chorus. The line style specifies the frequency range, with solid lines representing high frequency, dashed lines indicating medium frequency, and dotted lines denoting low frequency.

The frequency range per species is shown in Figure 1.6.

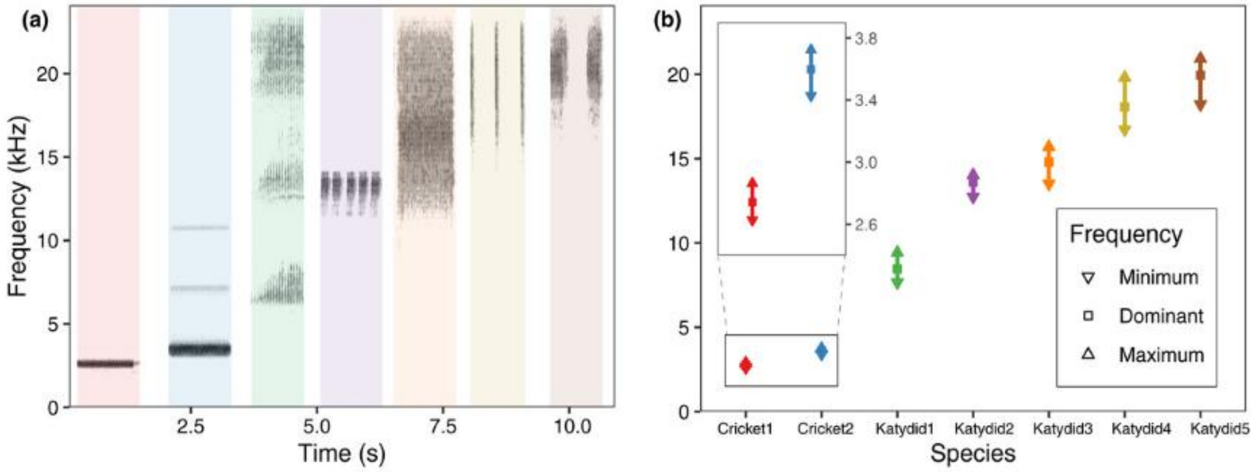



**Figure 1.6 Frequency range per species**

The average values are estimated for every 10,000 iterations. The relationships among the environmental observations with respect to acoustic detections are shown in Figure 1.7.

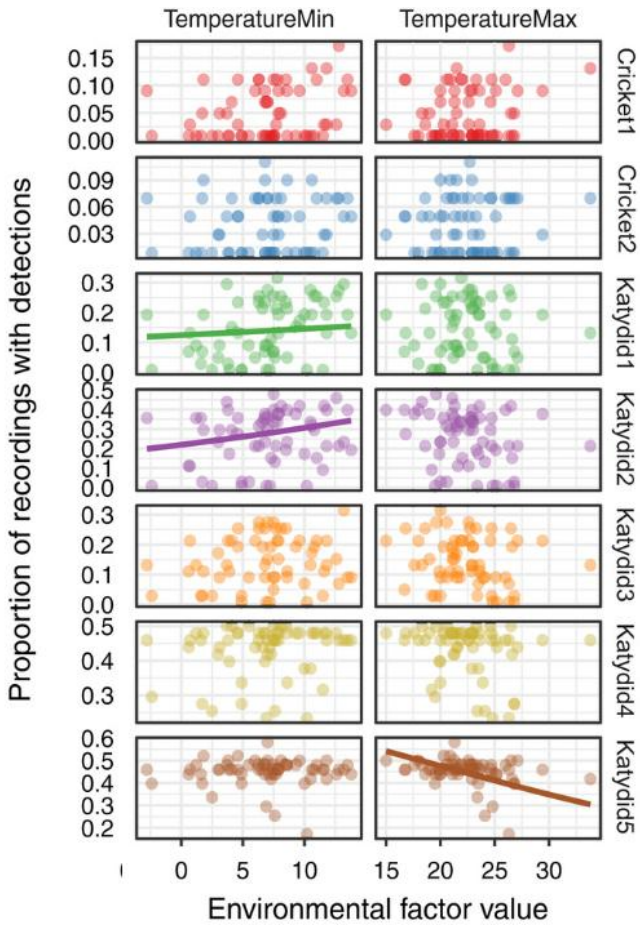



**Figure 1.7 Relationship between temperature and acoustic detections**

The process of pest detection is evaluated through the estimation of F1 score and precision– recall area. The incorrect detection deviates on precision–recall curve areas. Wavelet coefficients represent the strength of the signal at different scales and time points after wavelet decomposition. These coefficients capture information about the frequency content of the signal at various resolutions. This model of pest detection using RNN with LSTM is compared with CNN and SVM with the hold out of dataset split of 50% on training and 50% on test data. The evaluation of comparison is shown in Table 1.5.

**Table 1.5 Experimental Evaluation and Comparison of Pest Detection using acoustic data**

| Classifier Methods | Used Features | Performance F1 Score | The PR Area |
|---|---|---|---|
| SVM | Acoustic features (Wavelet) | 0.897 ± 0.020 | 0.934 ± 0.015 |
| CNN | | 0.913 ± 0.020 | 0.960 ± 0.015 |
| **RNN with LSTM** | | **0.922 ± 0.020** | **0.985 ± 0.015** |

The comparative analysis is shown as a graph below (Figure 1.8).

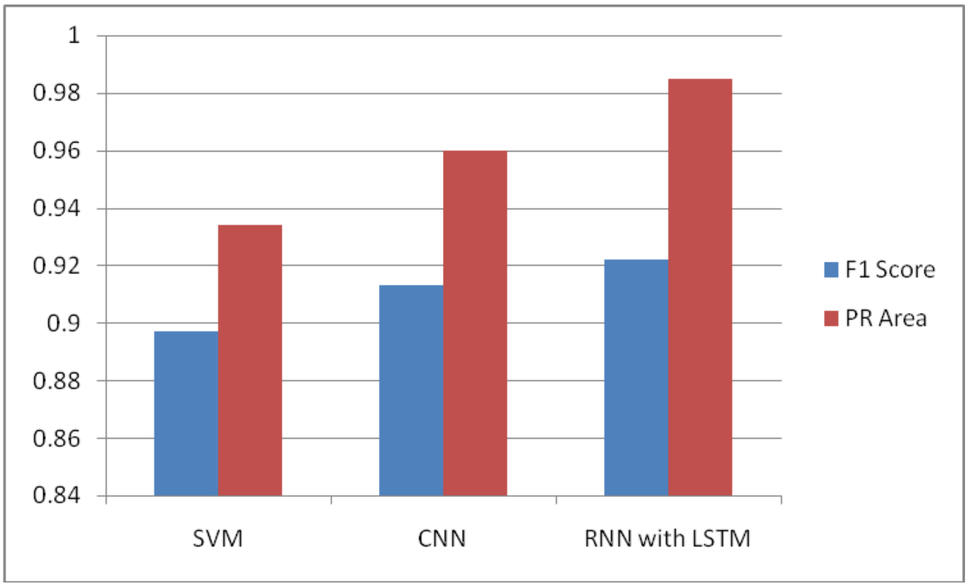



**Figure 1.8 Comparative analysis on evaluation of pest detection**

The graph at Figure 1.9 shows the comparison of normalized feature coefficient against wavelet coefficient.

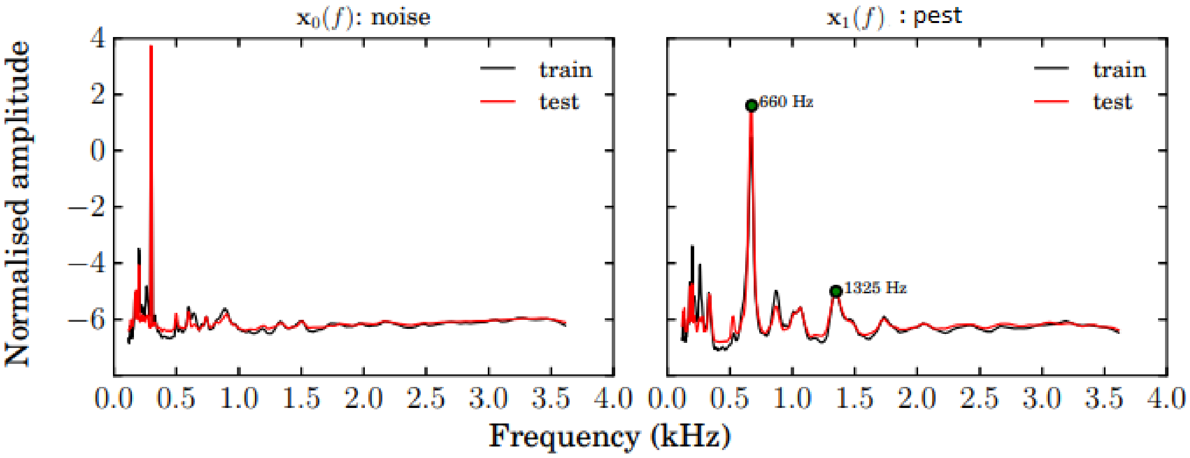



**Figure 1.9 Plot of normalised feature coefficient against wavelet frequency Four different experiments were conducted.**

**Experimental Setting 1: Fine Labels**

The classification efficacy and resilience is assessed by Signal-to-Noise Ratio (SNR) levels. This manipulation spans the spectrum from the threshold of detection to a distinctly audible level, involving a meticulous exploration of 8 discrete steps. In the pursuit of robustness, we conduct 40 iterations for each SNR setting. These iterations incorporate variations in both the temporal placement of injected signals. This experiment is done using Linear Discriminant Analysis (LDA) that uses linear combination of features, Gaussian Naive Bayes (GNB) follows an assumption that features are independent of given class, Support Vector Machine (SVM) that works on high-dimensional feature space, Random Forest (RF) that improves accuracy and controls overfitting, Multi Layer Perceptron (MLP) that uses regression, and Kernel Density Estimation (KDE) that can be used for anamoly detection.

The below figure 1.10 shows the evaluation of experiment 1 with fine labels. The noteworthy observation emerges as the machine learning models exhibit comparable performance, albeit with a slight yet meaningful competitive advantage demonstrated by the Gaussian Naive Bayes (GNB) model. The F1 score demonstrates a gradual increase, aligning with expectations, as the transition from the threshold of detection to more perceptible Signal-to-Noise Ratios (SNRs). In these challenging conditions, the test may fail based on selection. This sheds light on the nuanced challenges encountered when dealing with lower SNRs and emphasizes the importance of robust feature selection methodologies in maintaining model effectiveness.

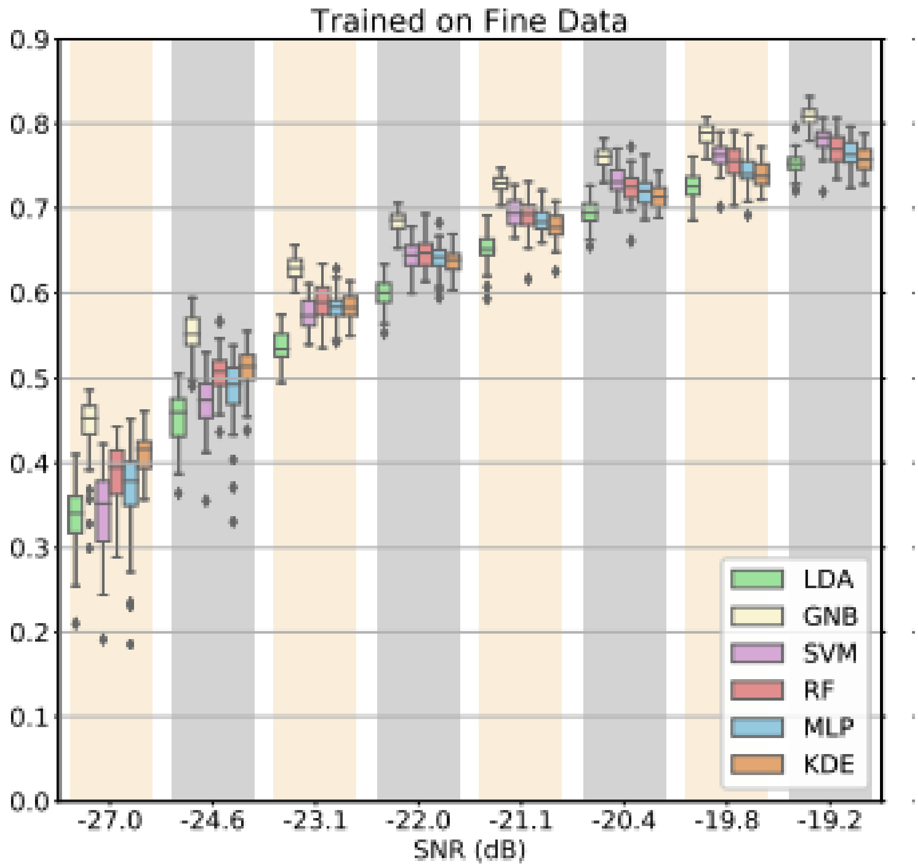



**Figure 1.10 Experiment evaluation and comparative analysis on finely labelled data**

**Experimental Setting 2: Median Filtering**

This experimental setting is associated with performing the training using Linear Discriminant Analysis (LDA), Gaussian Naive Bayes (GNB), Support Vector Machine (SVM), Random Forest (RF) etc. also performs the training on the same dataset with coarse class 0 data. Figure 1.12 showcases the process with median filtering.

A noteworthy performance boost surfaces for the Gaussian KDE, affirming that the implementation of temporal averaging proves instrumental in recovering event persistence. This manifests in the establishment of correlations between neighboring values in the time-series during an event. However, it's crucial to recognize that not every model reaps uniform benefits from this approach. Models characterized by high precision yet poor recall of the positive class with high F1 scores.

Conversely, the median filter overly high rate. And hence contribute positive F1 score with the impact of median filtering on overall performance.

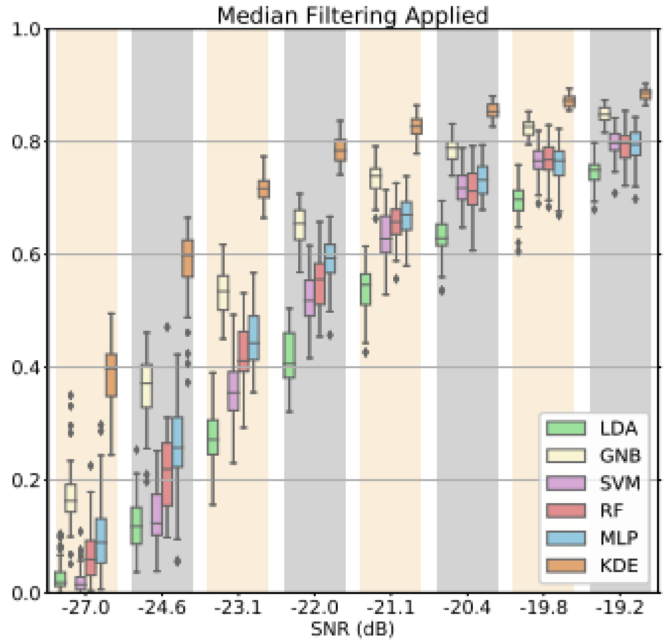



**Figure 1.12 Experiment evaluation and comparative analysis with applied median filtering**

**Experimental Setting 3: Rejection and Median Filtering**

In Figure 1.13, a compelling revelation unfolds as the Gaussian Kernel Density Estimation (KDE) emerges as a superior predictor of well-calibrated probabilities when compared to other baseline classifiers. The rejection window is set between 0.1 and 0.9. Notably, the Gaussian KDE demonstrates a significant performance improvement with low SNR.

Figure 1.14 illuminates the proportion of data that undergo rejection, uncovering a distinctive characteristic of the Gaussian KDE. At lower SNRs, the model rejects a substantial portion of the data, underscoring that extreme probabilities are assigned only when the model exhibits a high degree of confidence in its predictions. This nuanced behavior underscores the discriminative power of the Gaussian KDE in offering well-calibrated probabilities, particularly in challenging acoustic environments.

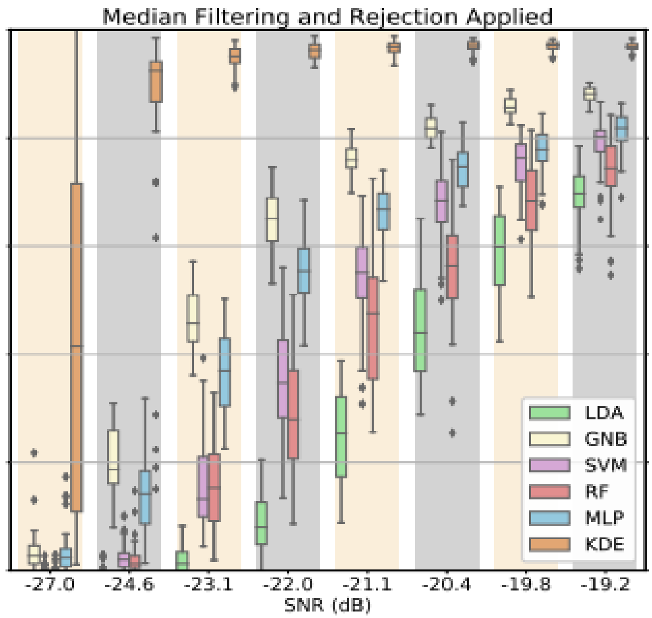



**Figure 1.13 Experiment evaluation and comparative analysis with median filtering.**

The Kernel Density Estimation (KDE) derives notable advantages from both median and rejection filtering, owing to its balanced distribution of positive and negative predictive accuracy, as well as its principled approach to handling uncertainty.

This dual application enhances the overall robustness and reliability of the KDE model, showcasing its adaptability and effectiveness in scenarios with varied levels of uncertainty and prediction complexities.

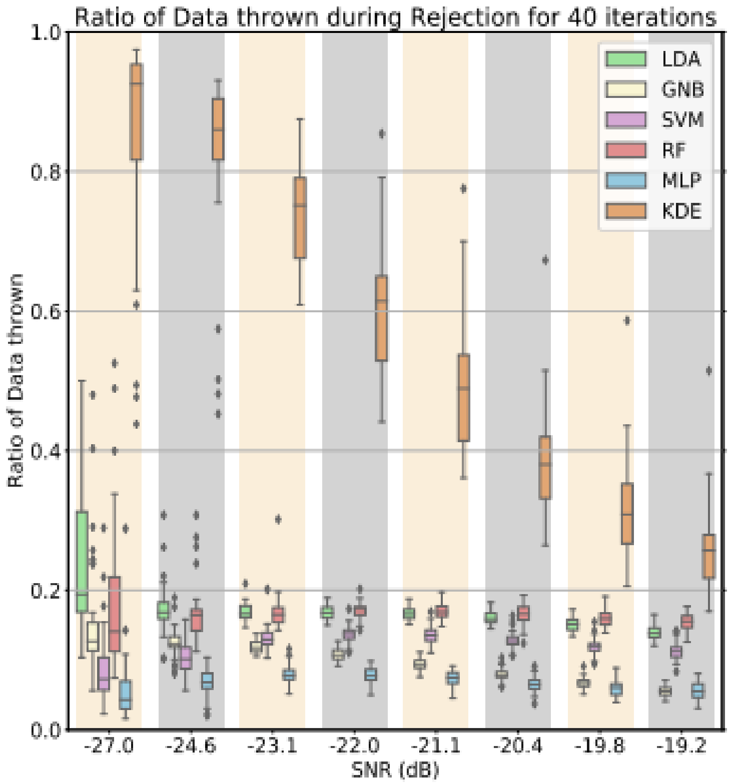



**Figure 1.14 Experiment evaluation and comparative analysis on ratio of data rejected by grouping SNR**

**Experimental Setting 4: CNN Classification**

This experiment delves into formal classification by applying median filtering and rejection on the comprehensive framework with the provision of pseudo-fine labelled data as input for Convolutional Neural Network. Table 1.6 presents data with conventional CNN trained on coarse data.

Training the CNN using Gaussian Kernel Density Estimation yields the best baseline system, the CNN(GNB), by an impressive 22.1%. The KDE exhibits lower precision and recall scores. This innovative approach showcases a significant advancement in the robustness and efficacy of the overall classification system.

**Table 1.6 CNN Classifier with 60 iterations**

| Classifier Methods | Performance F1 Score | Performance Precision | Performance Recall |
|---|---|---|---|
| **CNN with KDE** | **0.737 ± 0.036** | **0.720 ± 0.030** | **0.745 ± 0.032** |
| CNN with MLP | 0.438 ± 0.024 | 0.668 ± 0.027 | 0.323 ± 0.027 |
| CNN with RF | 0.325 ± 0.033 | 0.421 ± 0.036 | 0.262 ± 0.033 |
| CNN with SVM | 0.339 ± 0.025 | 0.486 ± 0.023 | 0.261 ± 0.023 |
| CNN with GNB | 0.596 ± 0.024 | 0.657 ± 0.027 | 0.546 ± 0.024 |
| CNN with LDA | 0.308 ± 0.028 | 0.572 ± 0.025 | 0.230 ± 0.027 |
| CNN with Coarse | 0.175 ± 0.037 | 0.094 ± 0.032 | 0.926 ± 0.041 |

The graph analysis on above comparison is depicted in Figure 1.15. It shows that CNN with KDE is the strongest inner classifier in terms of pest classification.

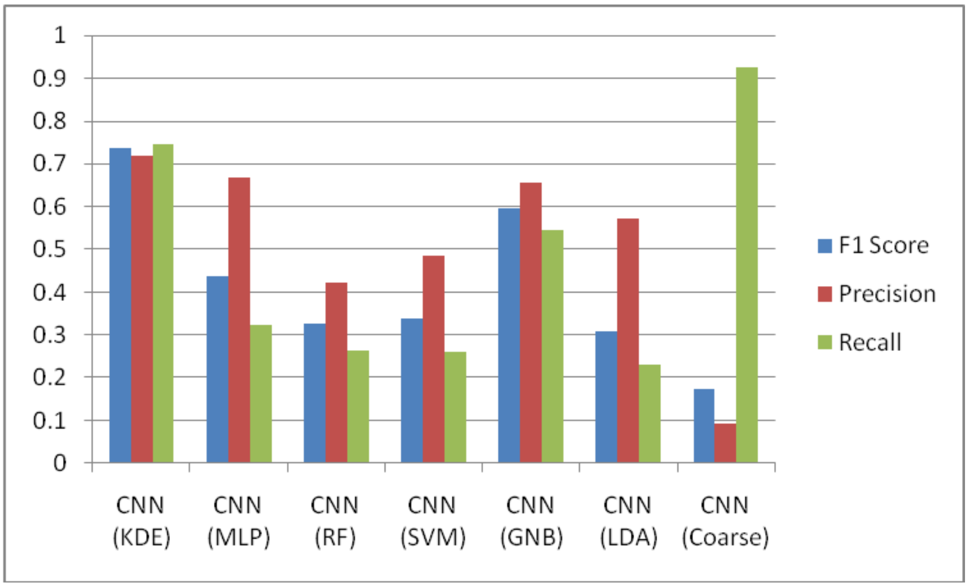



**Figure 1.15 Comparative analysis on Performance of CNN classifiers**

## 5. CONCLUSION AND FUTURE SCOPE

In conclusion, this article pioneers the integration of Smart IoT devices and cutting-edge deep learning and generative AI techniques for automatic pest detection in the realm of smart agriculture. The proposed smart system uses several IoT sensors enhances pest identification but also provides valuable details regarding the pest ecosystem in farming. Through the implementation of advanced deep learning models, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) with Long Short-Term Memory (LSTM), the article demonstrates a meticulous analysis of collected data for precise pest identification. The chatbot inclusion to the smart system is automatically and dynamically trained with observed data and environmental features. The proposed smart system ensures the pest detection with high accuracy and performance in predictive analysis of the pests.

The scalability and large-scale deployments of the proposed system is still a challenging issue. To ensure adaptiveness and swift response using the chatbots, rigorous training with more data is essential. If the smart system includes hyper spectral imaging and drone-based monitoring, the pest detection system will be attracting more farmers in the nation

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