engineering proceedings

MDPI

Proceeding Paper

Deep Learning-Enabled Pest Detection System Using Sound Analytics in the Internet of Agricultural Things †

Rajesh Kumar Dhanaraj [1] and Md. Akkas Ali [2,3,*]

[1] Symbiosis Institute of Computer Studies and Research, Symbiosis International (Deemed University), Pune 412115, India; rajesh.dhanaraj@sicsr.ac.in
[2] School of Computing Science and Engineering, Galgotias University, Greater Noida 201310, India
[3] Bangabandhu Sheikh Mujibur Rahman Science and Technology University, Gopalganj 8100, Bangladesh
* Correspondence: md.21scse3010038@galgotiasuniversity.edu.in
† Presented at the 10th International Electronic Conference on Sensors and Applications (ECSA-10), 15–30 November 2023; Available online: https://ecsa-10.sciforum.net/.

Abstract: Around the globe, agriculture has grown to a point where it is now a financially feasible way to produce more sophisticated cultivation methods. Throughout the long tradition of agriculture, this represents a pivotal moment. The widespread adoption of data and the latest technological advances in the contemporary period allowed this paradigm change. However, pests remain to blame for significant harm done to crops, which has a detrimental impact on finances, the natural world, and society. This highlights the necessity of using automated techniques to apprehend pests before they cause widespread harm. Agriculture-related issues are currently the predominant subject for research that utilizes ML. The overarching aim of this investigation is the development of an economically feasible method for pest detection in vast fields of crops that IoT enables through the use of pest audio sound analytics. The recommended approach incorporates numerous acoustic preparation methods from audio sound analytics. The Chebyshev filter; the Welch method; the non-overlap-add method; FFT, DFT, STFT, and LPC algorithms; acoustic sensors; and PID sensors are among them. Eight hundred pest sounds were examined for features and statistical measurements before being incorporated into Multilayer Perceptron (MLP) for training, testing, and validation. The experiment's outcomes demonstrated that the proposed MLP model triumphed over the currently available DenseNet, VGG-16, YOLOv5, and ResNet-50 approaches alongside an accuracy of 99.78%, a 99.91% sensitivity, a 99.64% specificity, a 99.59% recall, a 99.82% F1 score, and a 99.85% precision. The significance of the findings rests in their potential to proactively identify pests in large agricultural fields. As a result, the cultivation of crops will improve, leading to increased economic prosperity for agricultural producers, the country, and the entire globe.

Keywords: Internet of Agricultural Things; deep learning; Multilayer Perceptron; pest detection; sound analytics

Citation: Dhanaraj, R.K.; Ali, M.A. Deep Learning-Enabled Pest Detection System Using Sound Analytics in the Internet of Agricultural Things. *Eng. Proc.* **2023**, *58*, 123. https://doi.org/10.3390/ecsa-10-16205

Academic Editor: Francisco Falcone

Published: 15 November 2023

1. Introduction

Intelligent agriculture monitoring systems collect real-time agricultural data via IoT sensor networks [1]. Agriculture's production, efficiency, and sustainability are improved via automation and artificial intelligence. IoT devices use small sensors to measure soil moisture, temperature, humidity, light intensity, air quality, crop health, and water levels. These sensors are deliberately placed across a farm to collect data from multiple places. Internet-connected sensors use Wi-Fi, Lo-RaWAN, cellular, or satellite networks [2]. This link allows data to be easily transmitted to the cloud. IoT sensors are stored, analyzed, and processed in the cloud. Cloud computing features include scalability, real-time data access, and secure storage. The cloud platform discovers machine learning and analytics [3]. Estimates of crop health, appropriate watering regimens, and early disease and pest detection are examples of these findings. Farmers and agriculturalists can access real-time data via simple smartphone apps and web dashboards [4]. They use these networks to monitor their crops and farms remotely.

Pest management and irrigation systems can be automated using research and ideas. Data-driven farmers save money and resources [5,6]. They improve irrigation, fertilization, and other agricultural practices to boost crop output. Water and the environment are conserved via efficient fertilizer and water use. Early pest and disease detection prevent mega-outbreaks and crop losses. Remote agriculture gives farmers independence. Sustainable farming techniques decrease waste and resource usage [7–9]. This study proposes a real-time pest detection method using MLP and sound analytics. Technology will improve insect monitoring and treatment, making farming more efficient and environmentally friendly [10,11].

2. Dataset and Data Pre-Processing

The Agricultural Research Service (ARS) of the United States Department of Agriculture (USDA) is responsible for keeping the sound pest library, which is located at [12]. The sound recordings in this library were gathered using various acoustic sensors to record the sounds produced by various insect species. A network of IoAT devices over large agricultural areas can record pest sounds. The suggested technique analyzed 800 audio recordings of 16 pests, as indicated in Figure 1. The Chebyshev filter denoised pest audio data; the Welch approach reduced audio spectrum leakage; the non-overlap-add method transformed overlapping frames into non-overlapping ones; FFT, DFT, and STFT transferred time to the frequency domain and characterized and analyzed pest audio data for fusing with a recommended deep learning system model; and LPC extracted features from pest audio sound signals. The GMM calculated statistical measurements. In total, 70% of the data were used for training, 20% for testing, and 10% for validation.

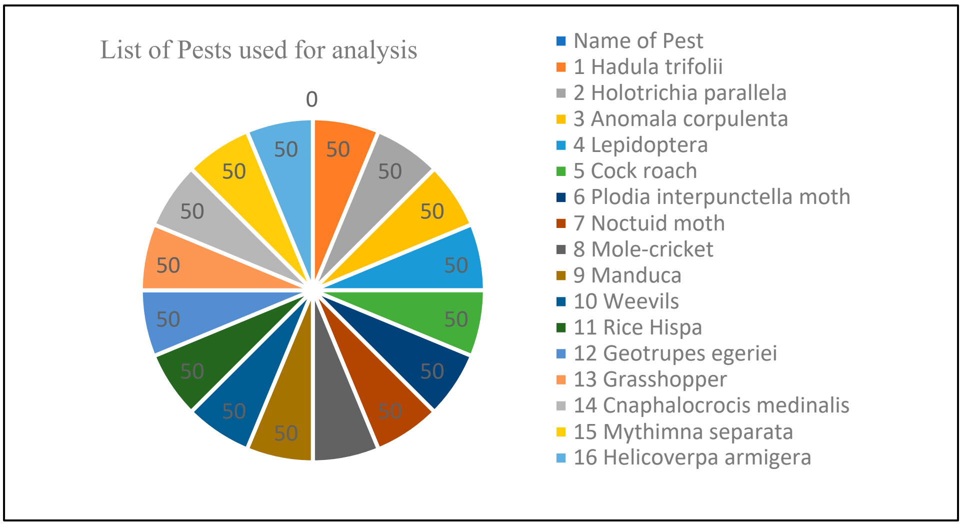


Figure 1. List of pests used for analysis.

3. Proposed Methodology

3.1. MLP System Model

We have used a fully lined 4-layered MLP as shown in Figure 2. Every computation abstraction layer has a fixed number of neurons. NN learns and weights neurons. The model layer sequence is input, first hidden, second hidden, output. The number of feature dataset input–output neurons create NN input and output layers. Based on identified ideas, inner layers have any number of neurons. The input layer has 20 nodes. It is 20*1. The improved first hidden layer has 40 neurons and ReLU. This layer's neurons weigh all input layer neurons. A 20*40 input-hidden layer connects the weight matrix. The 40-

neuron second hidden layer activates ReLU. Neurons are weighted to all first hidden-layer outputs. The first and second hidden layers' linking weight matrix is 40*40. The fourth layer, output, contains instantaneous input feature labels in 16 nodes, 1 per class. The output layer activates the sigmoid. Each node has all second hidden-layer neurons with output layer weights. The second hidden and output layers have a 40*16 linking weight matrix. Equation (1) calculates the output of a neuron $Z(B_1)$ at the first hidden layer using the weighted average of all inputs and bias E_1 and $F_1(p)$ from Equation (2).

$$Z(B_1) = F_1(\sum_{i=1}^{20}(A_i M_i 1) + E_1) \tag{1}$$

$$F_1(p) = \begin{cases} 0, & 0 < p \\ p, & p \geq 0 \end{cases} \tag{2}$$

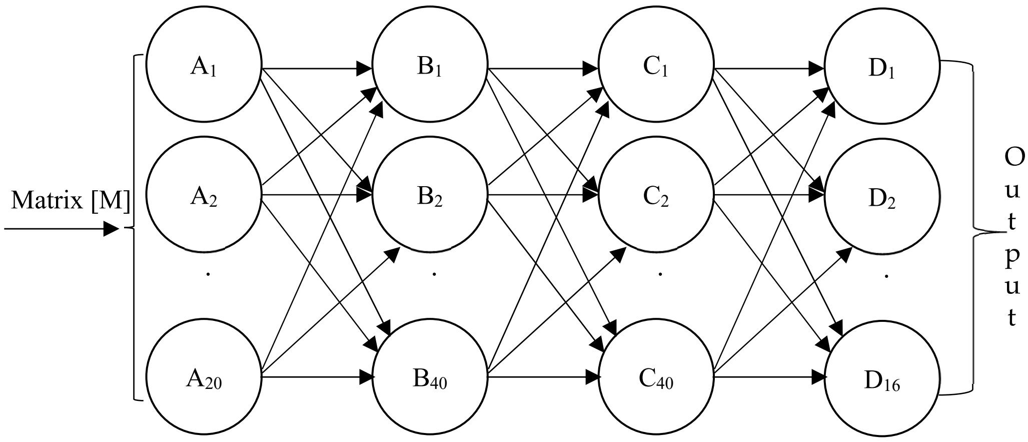


Figure 2. The architecture of the MLP system model.

The outcome of each neuron $Z(C_1)$ in the second hidden layer is supplied by Equation (3) and computed as the weighted average and E_2, which is assessed by $F_1(p)$, provided via Equation (2).

$$Z(C_1) = F_1(\sum_{j=1}^{40}(Z(B_j) M_j 1) + E_2) \tag{3}$$

In the end, D_1, provided via Equation (4), produced second layer outputs and bias E_3, assessed with $F_2(p)$, provided via Equation (5). The prediction output probability changed from 0 to 1.

$$D_1 = F_2(\sum_{k=1}^{40}(Z(C_k) M_k 1) + E_3) \tag{4}$$

$$F_2(p) = \frac{1}{1 + e^{-p}} \tag{5}$$

3.2. Architecture of the Proposed System

In big agricultural fields, it is feasible to identify pests by monitoring the sounds that pests produce and then comparing those sounds to data that have been gathered. This process is known as acoustic analysis. One can examine a sound to detect insects by comparing it with data already known in the database. These data should include sound processing information and should be analyzed with the help of the MLP system model and the sound analysis algorithm. Sending an agricultural pest's sound to the microcontroller analyses it to find the insects. If pests are unwanted, the PID sensor detects changes in their infrared emission (heat). The PID sensor can detect heat up to nine meters from an object above 0 degrees Celsius. The suggested system design is shown in Figure 3. After confirming that the invasive species is present in the field, acoustic sensors that cover the entire field are utilized to record pest sounds. After that, these noises are compared to a modified insect sound from the database. It uses sound-based technology to identify unwanted animals.

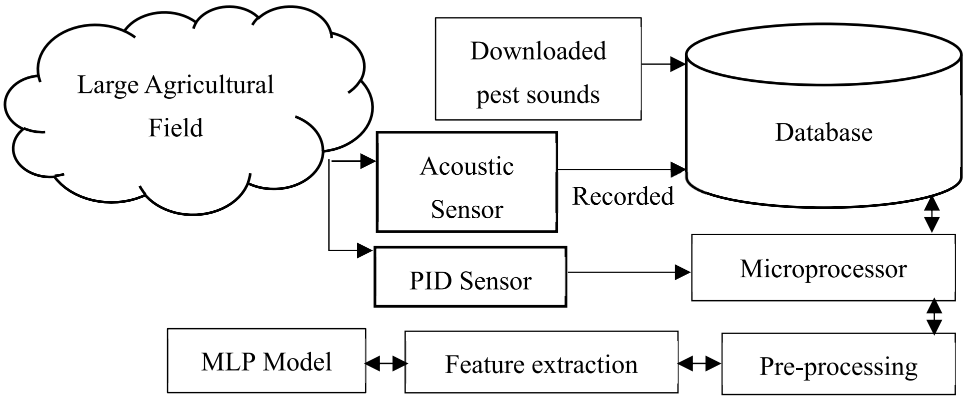


Figure 3. The architecture of the proposed system.

4. Experimentation, Results, and Analysis

4.1. Experimental Setup

For experiments, we used a computer with Windows 10, an Intel(R)Core (TM) i5-9300H processor at 2.40 GHz, 64 gigabytes of RAM, and a video card with additional effects. The study used Python 3.8.10 to simplify completion. Throughout the study, PyTorch 1.9.0 helped create the network model. Additionally, GPU acceleration with CUDA 10.2 increased computer graphics' computation power.

4.2. Performance Parameters

A different arrangement was assessed for general performance. Then, it was compared to the recommended solution, which used multiple methods to attain this goal. "True positive," "true negative," "false positive," and "false negative" were symbolized by their respective words.

$$\text{Accuracy} = \frac{(\text{TrueN} + \text{TrueP})}{(\text{TrueN} + \text{TrueP} + \text{FalseN} + \text{FalseP})} \text{ and Sensitivity} = \frac{\text{TrueP}}{\text{TrueP} + \text{FalseN}} \quad (6)$$

$$\text{Specificity} = \frac{\text{TrueN}}{\text{TrueN} + \text{FalseP}} \text{ and Reca} = \frac{\text{TrueP}}{(\text{FalseN} + \text{TrueP})} \quad (7)$$

$$\text{and Precision} = \frac{\text{TrueP}}{\text{TrueP} + \text{FalseP}}. \text{ and F1} - \text{score} = \frac{\text{Two} * \text{ precision} * \text{recall}}{\text{precision} + \text{recall}} \quad (8)$$

$$\text{MSE} = (1/\text{m}) * \Sigma\, (\text{a} - \text{f})^2 \quad (9)$$

$$\text{PE} = (\text{a} - \text{f}) * 100 \quad (10)$$

4.3. Results

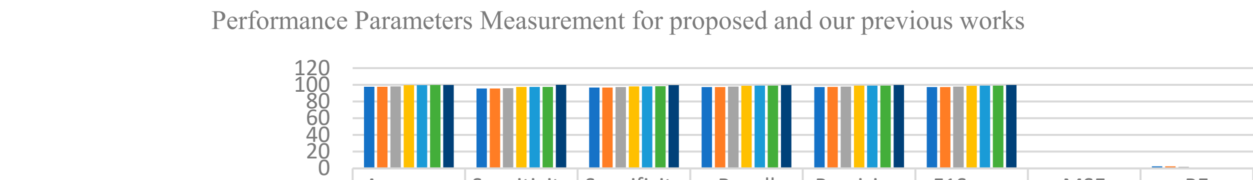
Table 1 presents the training, testing, and hypothesis testing data. The respective values of these percentages are 70, 20, and 10 percent.

Table 1. Samples were taken from the dataset.

Training Samples 70%	Testing 20%	Validating 10%	Total Samples
560	160	80	800

The accuracy scores, sensitivity scores, specificity scores, recall and precision scores, F1 scores, MSE scores, and PE values were generated by the MLP system model. These findings are presented visually in Figure 4. The presented MLP system model obtained accuracy ratings of 99.78%, 99.63%, and 99.76%, respectively, throughout the training, validation, and testing phases summarized and shown visually in Figure 5. As shown in

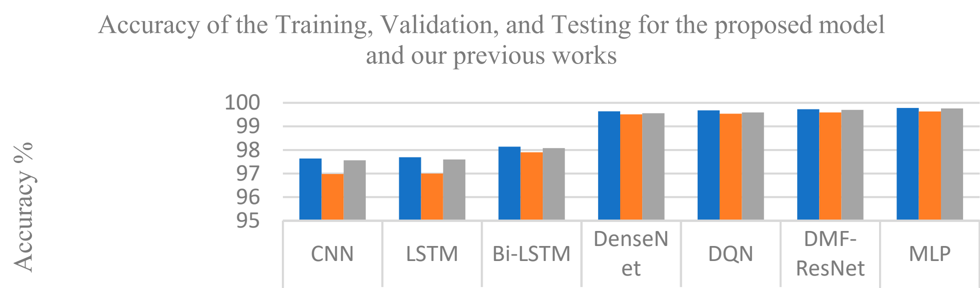
Figure 6, the recommended MLP system representation had impairments of 0.22, 0.37, and 0.24 throughout training, validation, and testing.



	Accuracy	Sensitivity	Specificity	Recall	Precision	F1Score	MSE	PE
Our Previous works CNN	97.64	95.55	96.72	97.3	97.38	97.32	0.0108	2.36
Our Previous works LSTM	97.69	95.58	96.74	97.32	97.41	97.36	0.0103	2.31
Our Previous works Bi-LSTM	98.14	96.03	97.19	97.77	97.86	97.81	0.0067	1.86
Our Previous works DenseNet	99.64	97.45	98.08	98.91	98.97	98.86	0.0002	0.36
Our Previous works DQN	99.68	97.53	98.14	98.93	99.03	98.94	0.0001	0.32
Our Previous works DMF-ResNet	99.73	97.57	98.22	98.96	99.08	98.98	0.0001	0.27
Proposed MLP	99.78	99.91	99.64	99.59	99.85	99.82	0.00007	0.22

Our Previous works CNN Our Previous works LSTM Our Previous works Bi-LSTM
Our Previous works DenseNet Our Previous works DQN Our Previous works DMF-ResNet
Proposed MLP

Figure 4. Performance parameter measurement for our proposed and previous works.



	CNN	LSTM	Bi-LSTM	DenseNet	DQN	DMF-ResNet	MLP
	Our Previous Works						Proposed
Accuracy (%) Training	97.64	97.69	98.14	99.64	99.68	99.73	99.78
Accuracy (%) Validation	96.98	97	97.9	99.51	99.54	99.59	99.63
Accuracy (%) Testing	97.56	97.6	98.08	99.56	99.59	99.7	99.76

Accuracy (%) Training Accuracy (%) Validation Accuracy (%) Testing

Figure 5. Training, validation, and testing accuracy for our proposed and previous works.

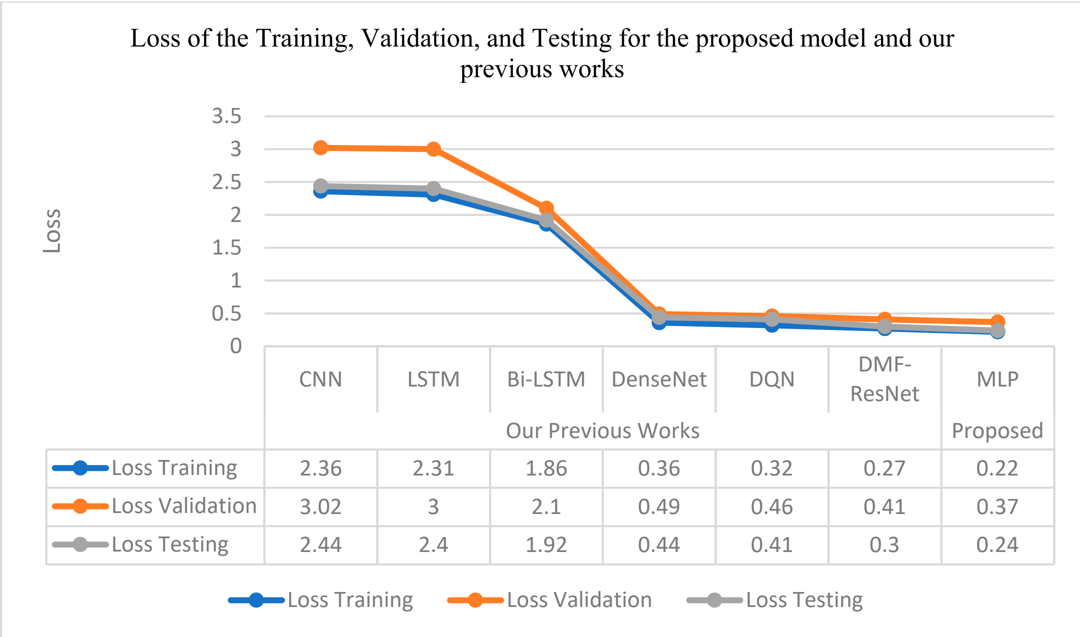


Figure 6. Training, validation, and testing loss for the proposed model and our previous works.

4.4. Performance Comparisons

Figure 7 presents an exposition of what was found in an investigation comparing the currently proposed research initiatives and the state-of-the-art methods.

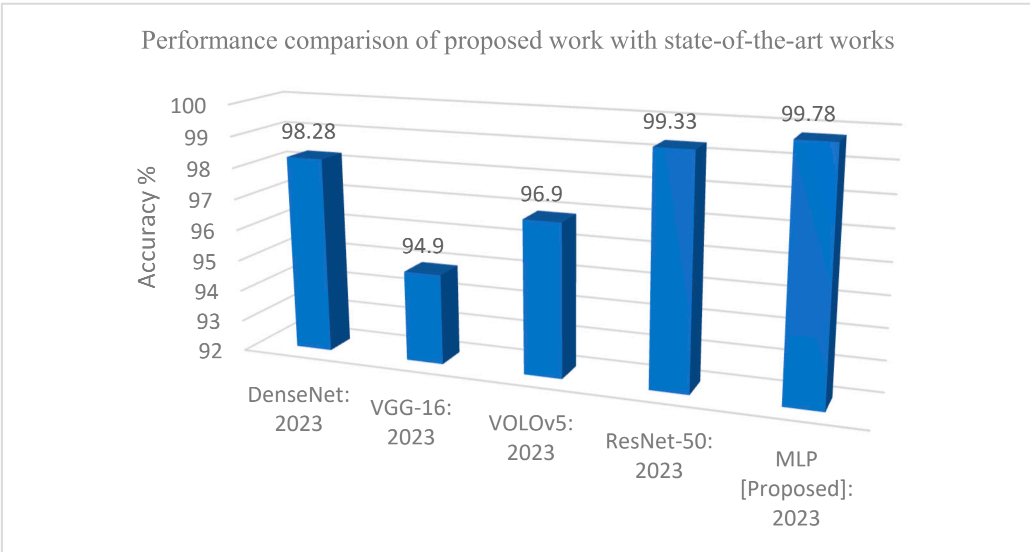


Figure 7. Performance comparison of proposed work with state-of-the-art works.

5. Limitations of the Proposed System and Future Scope

The proposed system used only 16 pest species and had a 99.78% detection rate; this is a limitation. With at least 100 pests, the suggested approach is expected to detect 100% soon.

6. Conclusions

We present the most data-driven, scientifically sound, and technologically advanced agricultural data ever. Agricultural IoT has made farming wise. This calamity transformed farming and opened doors. The problems farmers encounter limit agricultural productivity. Bugs, mites, and others cost agriculture a lot. Pesticides help farmers control weeds, plant-killing pathogens, and illnesses. Pesticides harm the environment, health, and the economy.

This study built an MLP-based, IoT-based autonomous real-time insect surveillance system. The IoT and sound analytics reduce pesticide use. Sound analytics can establish a pest's field presence by recording its sound.

Author Contributions: All authors have equal contributions. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Gupta, B.; Madan, G.; Md, A.Q. A smart agriculture framework for IoT-based plant decay detection using innovative croft algorithm. *Mater. Today Proc.* **2022**, 4758–4763. [CrossRef]
2. Siddiquee, K.N.E.A.; Islam, M.S.; Singh, N.; Gunjan, V.K.; Yong, W.H.; Huda, M.N.; Naik, D.B. Development of IoT-based smart agriculture monitoring system algorithms. *Wirel. Commun. Mob. Comput.* **2022**, *2022*, 7372053. [CrossRef]
3. Vangala, A.; Das, A.K.; Chamola, V.; Korotaev, V.; Rodrigues, J.J. Security in IoT-enabled smart agriculture: Architecture, security solutions, and challenges. *Clust. Comput.* **2023**, *26*, 879–902. [CrossRef]
4. Pagano, A.; Croce, D.; Tinnirello, I.; Vitale, G. A Survey on LoRa for Smart Agriculture: Current Trends and Future Perspectives. *IEEE IoT J.* **2022**, *10*, 3664–3679. [CrossRef]
5. Qazi, S.; Khawaja, B.A.; Farooq, Q.U. IoT-equipped and AI-enabled next generation smart agriculture: A critical review, current challenges, and future trends. *IEEE Access* **2022**, *10*, 21219–21235. [CrossRef]
6. Lovesum, J.; Prince, B. A Study on Experimental Analysis of Best Fit Machine Learning Approach for Smart Agriculture. *SN Comput. Sci.* **2023**, *4*, 187. [CrossRef]
7. Shaikh, T.A.; Mir, W.A.; Rasool, T.; Sofi, S. Machine Learning for Smart Agriculture and Precision Farming: Towards Making the Fields Talk. *Arch. Comput. Methods Eng.* **2022**, *29*, 4557–4597. [CrossRef]
8. Gong, H.; Liu, T.; Luo, T.; Guo, J.; Feng, R.; Li, J.; Guo, Y. Based on FCN and DenseNet Framework for the Research of Rice Pest Identification Methods. *Agronomy* **2023**, *13*, 410. [CrossRef]
9. Zhu, D.; Xie, L.; Chen, B.; Tan, J.; Deng, R.; Zheng, Y.; Andrew, W.H. Knowledge graph and deep learning-based pest detection and identification system for fruit quality. *Internet Things* **2023**, *21*, 100649. [CrossRef]
10. Chu, J.; Li, Y.; Feng, H.; Weng, X.; Ruan, Y. Research on Multi-Scale Pest Detection and Identification Method in Granary Based on Improved YOLOv5. *Agriculture* **2023**, *13*, 364. [CrossRef]
11. Hadipour-Rokni, R.; Asli-Ardeh, E.A.; Jahanbakhshi, A.; Sabzi, S. Intelligent detection of citrus fruit pests using a machine vision system and convolutional neural network through transfer learning technique. *Comput. Biol. Med.* **2023**, *155*, 106611. [CrossRef]
12. Available online: https://data.nal.usda.gov/dataset/bug-bytes-sound-library-stored-product-insect-pest-sounds/resource/ff1b1ed6-5597-4494-be21-7205122dae63 (accessed on 1 January 2023).