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AgriGuard: Automated Pest Classification for Agriculture

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Abstract—
Agriculture plays a significant role in sustaining life and contributing to the economic prosperity of nations, particularly those with an agriculture-based economy like India, where it has a notable impact on the GDP. To ensure consistent and optimal harvests, substantial financial investments are directed toward agricultural development. However, pests, such as rodents and insects, pose a serious threat to crop growth by damaging the yield. Early detection of pests is critical in preventing widespread damage and ensuring crop health. A preliminary assessment of the crop's condition can be used to evaluate its strength and identify any signs of pest infestation. Once detected, timely intervention can prevent considerable losses in yield. The implementation of early detection methods allows for informed decisions regarding pest control and pesticide use, thereby preventing unnecessary pesticide application. This approach not only helps protect crops from harm but also contributes to sustainable farming practices by reducing the environmental impact of chemical treatments. Early pest detection thus becomes an essential strategy in modern agriculture to safeguard both economic interests and ecological balance.

Keywords— Machine Learning, Feature Extraction, Image Dataset, Deep Learning, Pesticides.

1. INTRODUCTION

Agriculture is fundamental to India's economy, providing both economic stability and a livelihood for over 60% of its population. This industry is vital for guaranteeing food availability, sustaining the livelihoods of countless individuals, and making a substantial contribution to the nation's economy. To achieve high crop productivity, essential agricultural inputs, including water, fertilizer, and pest management, are vital. However, a substantial challenge faced by Indian farmers is a lack of awareness in distinguishing between beneficial and harmful pests. This knowledge gap often leads to indiscriminate pest control measures that not only harm helpful species but also contribute to lower yields and greater financial losses due to unnecessary pesticide use.

In recent years, progresses in innovation, especially in artificial intelligence (AI) and computer vision, have opened modern conceivable outcomes for tending to these challenges. Profound learning methods, especially convolutional neural systems (CNNs), have demonstrated profoundly compelling in dealing with assignments like picture classification and protest location. These technologies hold great potential in agriculture, where image-based methods can be utilized to identify and classify pests accurately. By integrating such advanced technologies, farmers can make more informed decisions regarding pest control, ensuring that only harmful pests are targeted while beneficial organisms are preserved.

The application of CNNs and machine learning models can help farmers accurately distinguish between destructive pests and beneficial organisms. Accurate pest identification enables the implementation of targeted pest control methods, which helps decrease excessive pesticide use and mitigates both environmental and economic consequences. [5]. Moreover, the selective targeting of harmful pests enables farmers to preserve the ecological balance within their crops, fostering healthier plant growth and contributing to sustainable agriculture. AI-based pest detection is not only faster but also more reliable, enabling early interventions that can prevent extensive crop damage and associated economic losses.

Furthermore, the adoption of these AI-driven technologies in agriculture aligns with the broader goals of sustainable development. By minimizing pesticide use and conserving beneficial organisms, such technologies support environmentally friendly farming practices, which are essential for long-term agricultural productivity. The integration of AI tools into farming practices also has the potential to significantly boost crop yields, reducing economic risk and enhancing food security for the population. As these innovative solutions become more accessible to farmers across India, they promise to transform pest management practices and improve the sector's resilience against pest-induced losses.

Incorporation in deep learning-based pest detection systems in Indian agriculture represents a significant step toward improved crop productivity and economic growth. By bridging knowledge gaps in pest identification, this technology empowers farmers to make informed decisions, protecting both crop health and the environment. The long-term benefits of these advanced pest management strategies hold great promise for supporting India's agricultural sustainability and strengthening its position in the global economy.

2. LITERATURE SURVEY

Ullah et al. (2022) Presenting the DeepPestNet model, a sophisticated deep learning architecture specifically designed for identifying and classifying crop pests. The authors tackle key challenges in pest management, including issues like misclassification and limited data availability. DeepPestNet is organized with 11 layers, comprising of eight convolutional layers and three completely associated layers, permitting it to successfully recognize complex designs in bother symbolism. Evaluated using the Deng dataset, the model demonstrated impressive accuracy, surpassing established models such as Squeeze Net and Google Net [6]. The study emphasizes the model's generalizability, supported by data augmentation techniques to bolster training data, resulting in robust and scalable performance for real-world agricultural applications.

The study by Kumari et al. (2024) explores the potential of deep learning for enhancing agricultural productivity through precise pest classification and pesticide recommendation. The authors highlight the shortcomings of traditional pest management methods, which often involve extensive labor and environmental risks due to indiscriminate pesticide use. By employing CNNs, the study demonstrates that automated pest classification can achieve significant accuracy improvements. The integration of environmental data and crop characteristics further enables personalized pesticide recommendations, optimizing pest control while reducing chemical exposure. This approach represents a shift toward sustainable agriculture practices that protect crop yields and minimize environmental impact [9].

Malek et al. (2021) present a deep learning-based pest classification model developed to distinguish between harmful and beneficial pests in agriculture. The paper underscores the significance of accurate pest identification, especially in regions where traditional methods may lead to unnecessary pest extermination and reduced crop productivity [3]. The findings reinforce the advantages of deep learning over traditional models like SVM and KNN, showcasing enhanced precision and reduced time complexity.

3. RELATED WORK

Recent studies have emphasized the development of automated systems for pest identification and classification, leveraging machine learning, cross breed procedures. These methods strive to build precise solutions to detect pests that pose risks to crop health and agricultural productivity. The application of DL techniques in image recognition and classification has enabled improved accuracy in pest identification, which is essential for implementing targeted pest control measures. Research works have highlighted ML-based techniques as effective for pest categorization, yet these approaches often require manually crafted features and parameter adjustments, making them less adaptive in complex outdoor environments compared to DL models. Below is a summary of relevant studies and methods developed for pest classification and recognition, incorporating advancements in ML, DL, and hybrid approaches.

ML-based approaches have shown success in pest identification using classifiers trained on specific pest features [19]–[21]. These approaches generally consist of extracting features from pest images and then classifying them using various models. For instance, [22] employed ML-based techniques to categorize armyworm-infested and healthy corn areas using an Unmanned Aerial Vehicle’s dataset. This research utilized Gini-importance for feature selection, showing that RF outperformed other ML methods in classifying armyworm-infected corn. Similarly, an SVM-based system was proposed in [23] for detecting thrips in greenhouses. This approach utilized image processing techniques to analyze colour indices like Hue, Saturation and Intensity have been utilized to achieve efficient classification, resulting in a mean error rate of less than 2.25%. Another inquire about think about [24] investigated the application of Histogram of Situated Slope (Hoard) and Nearby Parallel Design (LBP) procedures for distinguishing tomato bugs, with Hoard beating LBP. However, pest recognition methods based on machine learning intensely depend on physically made highlights, which can compromise the system's robustness under varying environmental conditions.

DL approaches have seen increasing use in pest recognition, particularly convolutional neural networks (CNNs) due to their success in visual recognition tasks [25]–[27]. These techniques excel in learning image features automatically, removing the need for manual feature extraction. As illustrated in [15], a novel dataset for identifying crop pests was presented, and three deep learning models were trained utilizing transfer learning (TL) and fine-tuning techniques, achieving a recognition accuracy exceeding 80%. The study utilized gradient-weighted class activation to visualize critical recognition areas, focusing more on intricate details of the pest images rather than overall appearance, which improved classification performance. Another study [16] proposed a DL-based system that combined CNNs with hyperspectral imaging (HSI) for pest detection. This approach leveraged spectral feature extraction units that combined one-dimensional convolution with attention mechanisms across spectral channels. This design improved feature representation by effectively handling noise and reducing redundancy in the spectral domain. The HSI method incorporated three-dimensional convolution branches to preserve high-resolution features, offering detailed spectral-spatial information.

Hybrid methods, which integrate ML and DL models, have shown promise in enhancing classification accuracy for pest recognition tasks [28]. Bayesian optimization was applied for tuning hyperparameters, with the VGG16 model outperforming other architectures after image augmentation. Additionally, ResNet50, combined with a discriminant analysis classifier, achieved the highest accuracy, demonstrating the benefit of hybridizing CNNs with traditional ML classifiers. Another recent study [29] developed TPest-RCNN, a DL model based on a faster regional-CNN, which used VGG16 for feature extraction. This approach generated regions of small pests through a region proposal network, followed by classification, enhancing precision in identifying pest locations within images.

Despite the successes of DL models, their performance is often constrained by limited pest image datasets and challenges in interpretability. Most DL models for pest classification are tested under controlled laboratory conditions, which limits their generalizability to field settings where lighting, backgrounds, and pest orientations vary significantly. For example, research on natural scenes is scarce, and existing studies often focus on a single pest species or utilize limited datasets, which hampers the generalization of these models to diverse agricultural settings. Effective pest recognition systems in natural settings require resilience to variations in viewpoint, scale, and lighting, which is critical for real-world applicability. This research focuses on overcoming these challenges by creating a deep learning framework capable of classifying and identifying ten distinct pest categories under diverse environmental conditions to improve the generalizability of the show, we increased the dataset through picture turn and other information increase strategies, guaranteeing steady execution over different datasets. The model was evaluated on an additional dataset containing nine different crop pest types, further demonstrating its versatility and precision in real-world field environments. The proposed framework represents a step forward in creating robust, real-time pest detection systems for agricultural applications, promoting more effective and environmentally friendly pest management solutions.

4. METHODOLOGY

The methodology for developing an automated pest identification system involves several stages, beginning with data collection and progressing through model training, validation, integration, and testing. Each step is carefully structured to ensure that the final system is robust, accurate, and user-friendly.

A. Data Collection

Data collection forms the basis of this methodology, where a comprehensive and high-quality dataset of crop pest images is compiled from reputable agricultural databases. These databases provide a broad spectrum of pest images, including numerous species commonly found in India, which are essential for creating an effective machine learning model. [5]. Additional datasets are sourced from stages such as

Kaggle, especially those pertinent to Indian therapeutic plants. The upgraded dataset makes strides the model's capacity to precisely classify bugs in down to earth, real-world applications.

B. Dataset Characteristics

The dataset consists of thousands of images featuring various crop pests, collected under different environmental conditions and viewpoints. Each image is annotated with the corresponding pest species, creating an accurate ground truth for both the training and validation phases. These labels allow for supervised learning, ensuring that the model is trained effectively and can perform reliably when deployed. The dataset is structured to facilitate organized and thorough training, which enhances the model's adaptability and performance in practical applications.

The dataset comprises images that encompass a broad range of pest species found in India, which upgrades the model's capacity to generalize successfully over distinctive bug sorts. The images' high resolution and clarity support precise feature extraction, leading to more efficient model training.

Fig.2 Beneficial Pests[6]

Fig.3 Harmful Pests[6]

C. Diversity and Quality

The dataset includes a wide range of pest species, particularly those affecting Indian crops, enabling the model to generalize effectively across multiple pest types. High-resolution images with clear detail are selected to facilitate accurate feature extraction during training, which is essential for building a dependable pest identification system. The quality and diversity of images ensure that the model remains effective across different environmental conditions and pest species, supporting its deployment in agricultural settings.

D. Data Preprocessing

Data preprocessing is essential for preparing images for input into the ML model. This phase includes several key sub-tasks:

1) Resizing and Normalization: The pictures are resized to a uniform estimate of 224x224 pixels, and their pixel values are scaled to drop inside a run of to 1. This normalization guarantees that the input information is reliable, making strides the model's capacity to prepare the information successfully and advancing more steady training.

2) Data Augmentation: To increase robustness and prevent overfitting, data augmentation techniques are applied. Methods such as random rotations, translations, flips, and zooming add diversity to the dataset without additional data collection.

3) Dataset Splitting: The dataset is part into preparing, approval, and test sets, permitting for compelling demonstrate preparing and assessment. This partition guarantees a more solid appraisal of the model's execution at distinctive stages.

E. Model Selection

Pre-trained convolutional neural network system (CNNs), are chosen for this task because of their demonstrated success in image classification. These models, already trained on large datasets, are adapted to the pest dataset through transfer learning to enhance both accuracy and efficiency in pest identification.

1) Pretrained Model:

Leveraging transfer learning, pre-trained models initially trained on larger, general image datasets are fine-tuned to the pest dataset. This allows the model to retain essential learned features, accelerating training time and improving classification accuracy.

F. Training Using Transfer Learning:

Transfer learning is employed to refine pre-trained models, adapting them specifically to the pest dataset.

1) Fine-Tuning Process: The final classification layer of the pre-trained models is modified to match the pest species categories in the dataset. The models are then fine-tuned using the training data, allowing them to specialize in recognizing pests.

2) Hyperparameter Tuning: Basic hyperparameters such as learning rate, bunch estimate, and age number are optimized to upgrade show precision and effectiveness.

3) Optimization: The Adam optimizer is used to adjust model weights during training. Adam's adaptive learning rate helps manage sparse gradients and improves convergence speed, ensuring efficient learning throughout the training process.

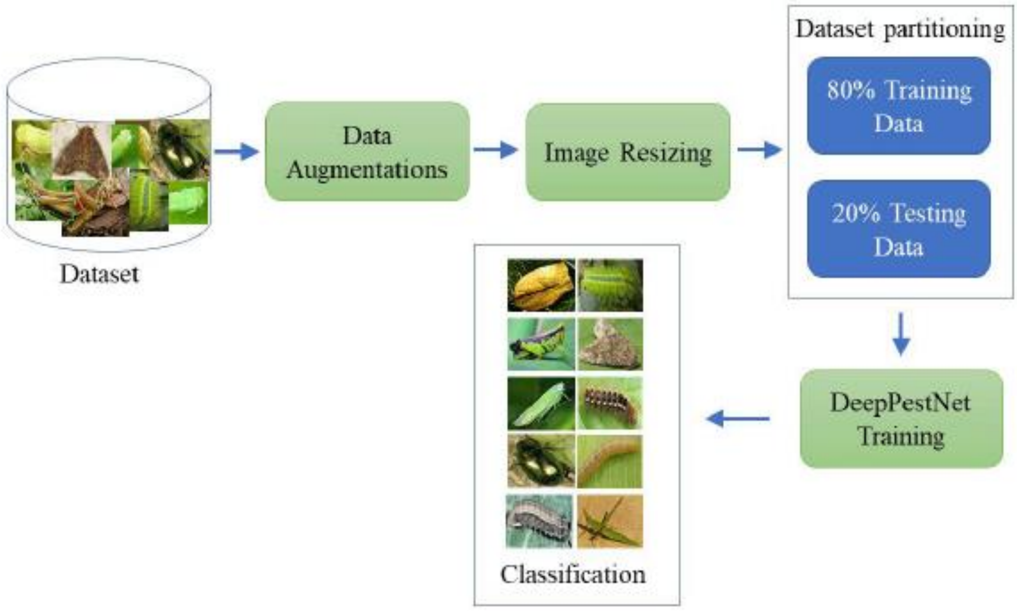

Fig.4 General workflow of the proposed system.

G. Model Validation

Validating the trained model is crucial to assess its performance and generalization ability across new data.

1.) Cross-Validation: K-fold cross-validation is utilized to evaluate the model's solidness and fluctuation by preparing it on different information subsets. This strategy gives bits of knowledge into how reliably the demonstrate performs over subsets.

2.) Validation Metrics: Essential measurements, counting precision, exactness, review, and F1-score, are utilized to assess the model's adequacy in bug distinguishing proof, giving a comprehensive evaluation of its execution.

3.) Confusion Matrix: A confusion matrix helps visualize performance by revealing specific classes where the model performs well or struggles. This analysis is valuable for identifying potential improvements.

H. Integration into an Android Application

The trained model is subsequently incorporated into an Android app, enabling its application in practical agricultural scenarios.

1) Model Conversion: For deployment on mobile devices, the model is transformed into the Tensor Flow Lite format. This format is optimized for performance in resource-limited environments, ensuring the application remains responsive and efficient on mobile devices.

2) Application Development: The application, built using Kotlin, enables users to either capture or upload images of pests, which are then analyzed by the model to produce identification results.

3) User Interface: A user-friendly interface is designed, presenting pest names and relevant information to support farmers and agricultural professionals in pest management.

The interface is structured to ensure ease of use, especially for non-technical users.

I. Testing

Thorough testing is conducted to confirm the reliability and usability of the application.

1) Functional Testing: Core functions, including image capture and processing, are tested to ensure they work as expected, allowing users to seamlessly interact with the app.

2) Performance Testing: The application is tested on a variety of Android devices to measure response time, memory usage, and overall efficiency. The testing ensures smooth operation across different hardware configurations.

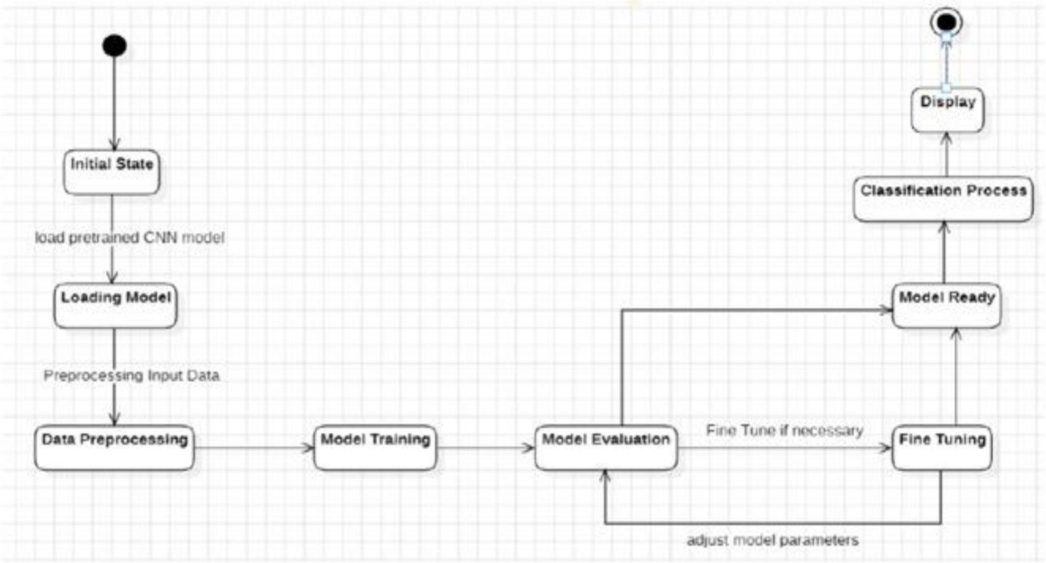

Fig.5 Model Training Flowchart

II. Materials

A. CNN

Convolutional Neural Networks (CNNs) plays a crucial role in deep learning methedology, especially in image classification applications. These systems for the most part comprise of three fundamental sorts of layers: the input layer, covered up layers, and the yield layer. The covered up layers can contrast in complexity, comprising of convolutional, pooling, completely associated, and normalization layers. The amount and arrangement of these layers are custom fitted to suit the complexity and requests of a particular problem.

B. Transfer Learning

1). VGG:

The VGG16 show, made by K. Simonyan and A. Zisserman, was displayed within the 2014 ILSVRC competition, where it accomplished a top-5 blunder rate of 7.3% on the ImageNet approval set. This architecture employs a series of stacked 3x3 convolutional filters to enhance the model's depth. The network's fully connected section comprises two layers with 4096 nodes each, followed by a final 1000-node layer configured as a SoftMax classifier. VGG16 and its counterpart, VGG19, share structural similarities but differ in the number of layers and parameters.

2).InceptionV3:

This architecture evolved from Google's development of the Inception series. InceptionV3, with 48 layers, is an advancement over its predecessors, capable of handling extensive datasets such as ImageNet, which contains over a million images. While similar to InceptionV1 and V2, InceptionV3 integrates additional optimization techniques that enhance performance during competitions like ILSVRC.

3).ResNet:

ResNet, which stands for Remaining Organize, revolutionized profound learning with its 50-layer design. At first discharged in 2015, it accomplished a top-5 mistake rate of 3.75% on the ImageNet dataset. A outstanding characteristic of ResNet is its joining of remaining associations, or easy route pathways, which help address the vanishing gradient issue and enable the construction of deeper neural networks. ResNet50 specifically includes three blocks of bottleneck layers, each comprising 34 sub-layers.

4).MobileNetV2:

Designed for use in mobile and embedded devices, MobileNetV2 employs an inverted residual structure, connecting thin layers through expansion and depth wise separable convolutions. Its design includes a first 1x1 convolutional layer activated by ReLU6, a depth wise layer, and a final linear 1x1 convolution layer to avoid non-linearity at the output.

5. Experimental Result

The system was assessed employing a test dataset to conduct tests over distinctive classification models. Different classification calculations and exchange learning with a few CNN designs were executed to survey execution. The tests delivered changed comes about in terms of classification exactness, with the proposed CNN show accomplishing the most noteworthy exactness at 90%. In comparison, the KNN model reached a classification accuracy of up to 81% (as shown in Fig. 5). Other classification models showed less promising results for pest prediction, indicating the proposed CNN's superior capability in identifying pests accurately .

Fig.6 Test accuracy [6]

A similar dataset was utilized for SVM classification task with an RBF part and a regularization parameter (C) set to 1. However, the resulting accuracy was only 64%, indicating suboptimal performance. Similarly, the Logistic Regression model using the "Mgs" solver also showed limited effectiveness, achieving a test accuracy of just 67%. In contrast, the KNN model, configured with three neighbours and utilizing the Minkowski metric, achieved better accuracy than both SVM and Logistic Regression. Despite these results, the proposed CNN model demonstrated superior test accuracy overall, making it most effective model for this pest classification assignment.

Classifiers	*Precision*	*Recall*	*F1-score*	*Accuracy*
SVM	.64	.64	.64	.64
LR	.67	.67	.67	.67
KNN	.83	.82	.82	.81
Proposed CNN	.90	.90	.90	.90

Table.1 Performance Matrices Report of Different Classifiers.[6]

6. RESULTS

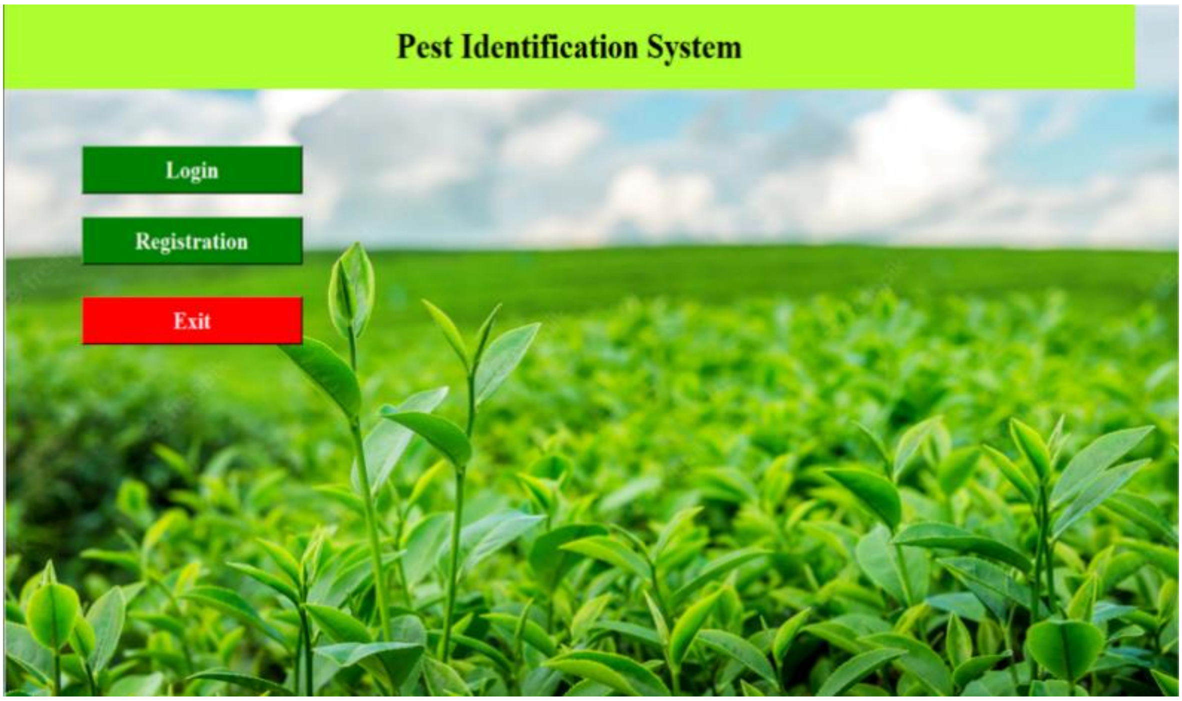

Fig.7 Home Page

The graphical interface of the system is structured to promote ease of use, featuring three primary interactive buttons: one for user authentication, another for account creation, and a final option for terminating the session. This layout is intentionally designed to facilitate straightforward navigation, enabling users to log in securely, initiate new user registrations, or exit the platform as needed. The simplicity of this design ensures accessibility and enhances the overall user experience, particularly for individuals with limited technical expertise.

Fig.8 Registration Page

Overall, integrating a well-structured registration mechanism is essential not only for maintaining data integrity and protecting sensitive information but also for ensuring a seamless, user-focused interaction model across modern web and software applications.

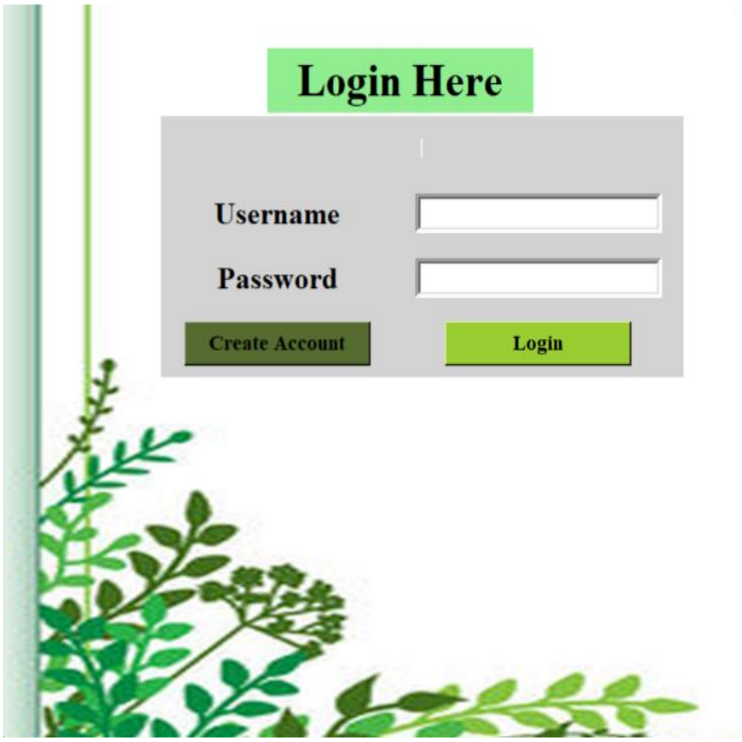

Fig.9 Login Page

A login interface is a fundamental component of digital security infrastructure, acting as the primary gateway through which authorized users gain access to an application or system. The minimalistic layout not only enhances the user experience but also reduces complexity, enabling seamless and efficient interaction.

Fig.10 User Interface

The visual interface depicted represents AgriGuard: Automated Pest Classification, an innovative digital platform designed to enhance the accuracy as well as efficiency of pest identification in agricultural settings. Selecting the Pest Identification function likely initiates, a process driven by advanced computational models, such as ML or DL techniques. These algorithms are typically trained on extensive image datasets to recognize and differentiate pest species from visual data.

Fig.11 Example of an Identified Pest using Prediction/Classification Algorithm

The displayed interface illustrates the operational layout of AgriGuard: Automated Pest Classification, an advanced digital platform leveraging artificial intelligence to transform pest detection practices in agriculture. The design of this interface follows a logical and user-oriented flow, enabling targeted users such as farmers, agricultural specialists, and scientific researchers to accurately identify pest species through visual data inputs.

Positioned on the left side is a vertically aligned menu containing four primary functionalities: Select Image, Image Pre-process, Train Model, and CNN Prediction. These features guide users through each stage of the classification pipeline—starting from uploading an image of the affected crop, refining the image for analysis, initiating model training, and ultimately producing a classification result using a CNN model.

Central to the interface is a visual sequence displaying three image stages: the unprocessed original, a grayscale conversion, and a binary segmented output. These progressive transformations reflect standard pre-processing techniques employed in computer vision to enhance feature extraction before analysis.

7. Conclusion

This project addresses the critical challenge of accurate pest identification by applying advanced deep learning techniques, including transfer learning, to enhance precision and efficiency. Conventional pest identification techniques are frequently inefficient, error-prone, and time-intensive, resulting in poor pest management and decreased agricultural yields. By leveraging pre-trained models, such as VGG and ResNet, customized with specific pest image datasets, this system offers an automated and highly accurate pest detection solution.

The inclusion of this model within an Android application further enhances its accessibility, providing farmers and agricultural professionals with a user-friendly platform for rapid pest identification. Extensive data preprocessing, model optimization, and rigorous validation have been implemented, ensuring the system's reliability and accuracy in real-world settings. This approach promotes not only more efficient pest management but also supports sustainable agriculture by enabling targeted pest control, reducing unnecessary pesticide use, and enhancing crop productivity. This system represents a recognizable step forward in pest identification with management, fostering more eco-friendly agricultural practices. By contributing to more sustainable and efficient pest control, it helps in achieving higher crop yields while minimizing environmental impact. Overall, the project has the potential to greatly benefit agricultural productivity and supports the broader objective of eco-friendly and sustainable farming practices.

8. Future Scope

For future improvements, expanding the pest database to include a wide spectrum of species, including rare also region-specific pests, is crucial for enhancing the model's generalization and adaptability to different agricultural environments. Such an expansion will improve the system's accuracy across diverse crop types and regions. In addition, optimizing the model for greater efficiency will reduce computational demands and enable its deployment on devices with limited processing power, such as smartphones commonly used in rural farming communities. Integrating Internet of Things (IoT) devices, like smart cameras and drones, can enhance pest monitoring by delivering real-time notifications and pest control suggestions directly on-site. This integration will help farmers make more informed decisions for effective pest control. Multilingual support could broaden the tool's accessibility, making it easier for farmers from various linguistic backgrounds to utilize the system. Additionally, offline functionality will be essential for rural areas with limited internet connectivity, allowing the system to work reliably without a constant internet connection. Expanding the system to include crop disease identification alongside pest detection will provide a more comprehensive solution for farmers. Using similar deep learning techniques, the system could help detect and manage both pests and diseases, contributing to better overall crop health and enhanced agricultural productivity.

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