

## ***An Explainable AI-Driven Hybrid Deep Learning Model Integrating Lightweight CNN And Neural Architecture Search Network For Precision Agriculture Applications***

Mahesh Kumar Tiwari<sup>1</sup>, Harsh Dev<sup>2</sup>

<sup>1</sup>Department of Computer Science & Engineering Babu Banarsi Das University, Lucknow, India.

<sup>2</sup>Department of Computer Science & Engineering Babu Banarsi Das University, Lucknow, India.

Email: maheshyogi26@gmail.com, drharshdev@gmail.com

### ***Abstract***

Crop productivity is most important in the economic growth and development of the world. Unfortunately, productivity is on the decline while the population keeps growing, making it more challenging to produce food globally. There are several factors that contribute to the decaying productivity, including desertification, crop crises, among others. Here in this paper, we concentrate on crop crises due to plant diseases. These illnesses have a significant effect on crop yields, but they can be controlled and managed using conventional practices and AI-based contemporary techniques. Conventional practices are time-consuming and cannot always ensure the best outcomes, while AI-based methods like deep learning can yield more precise and timely results. Various pre-trained models like Alex-Net, VGGNet, Inception-Net, and ResNet have proved to be very accurate—usually over 90%—when it comes to classification problems. Yet these models are computationally expensive and require high memory and computational resources, which is resource-intensive in some environments. In order to solve these problems, this paper introduces a hybrid model, drawing on principles of Explainable AI in an attempt to provide optimized outcomes cheaply and within a reasonable timeframe. XAI has the major advantage over simply using pre-trained models by increasing the transparency and trustworthiness of the decision-making process. XAI techniques allow researchers and farmers to see what areas of the potato leaf the model is looking at when making a prediction of a disease and aid in checking if the model is learning actual patterns of diseases or getting misled by irrelevant features such as background noise. This insight aids in better model tuning, increases user trust, and leads to more reliable and helpful disease control in real farming conditions.

**Keywords** Plant Diseases, Deep-learning, Lightweight CNN, Neural Architecture Search Network, Hybrid model, Explainable AI.

### ***1. Introduction***

Every single civilization is founded upon agriculture. It was once predominant, yet due to a series of variables, climatic, political, social, and environmental among them, its production has been on the decline throughout the years [1]. Furthermore, potatoes are a basic food requirement that can be produced in most parts of the world. As indicated in a recent study, China is leading in potatoes production globally with an estimated production of 90,321,442 tons each year. The second, third, and fourth major producers of potatoes are India with an estimated production of 48,529,000 tons, Ukraine with 22,503,970 tons, and Ireland with 273,000 tons, respectively [2].

Among the numerous crops grown worldwide, potatoes are special in that they are staple foods and have a significant role to play in world agriculture. Apart from their distinctive appearance, potatoes are crucial to the world population's sustainability. Their adaptability ensures a constant supply of vital nutrients and meets the nutritional needs of many geographical regions. Potatoes are a critical crop for achieving world food

security due to their nutrient density and versatility [3]. These plant pests and diseases, usually caused by fungi, bacteria, viruses, and other diseases, have huge effect on the quality and quantity of the crop. Taking preventative measures and reducing financial and production losses depend on early detection. Detection of disease has long been based on trained visual observation that is labour-intensive and susceptible to errors. [4]

Alternatively, it has been found that the development of image analysis software is a good method for early disease diagnosis in plants. In general, diseases usually present characteristic symptoms on the leaves, so that different deep learning methods can be used for disease detection and identification [5]. Machine learning approaches, in particular deep learning, revolutionized computer vision by successful progress with object identification and classification. Such breakthroughs are enabled by Convolutional Neural Networks, where VGG, ResNet, and Inception models have established performance standards. However, with the increasing demand for high precision and low computational costs, various hybrid and lightweight model designs arose based on the performance and reduced computational cost trade-off.

Here, we compare the proposed hybrid model using explained AI, comprising NASNet and light-weight CNNs with other deep learning frameworks. NASNet uses reinforcement learning-based architecture search to maximize model performance, while the light-weight CNNs are engineered to reduce computational complexity at the expense of limited loss in accuracy. It is this integration of both techniques that is aimed at taking the best of both worlds—high accuracy with low complexity. This work compares the hybrid model with traditional deep learning models in performance based on accuracy, computational complexity, and generalization capability. We conducted extensive experiments to provide insight into whether the hybrid NASNet-Lightweight CNN model performs better compared to conventional architectures and presents a solution for real-time applications with limited computational resources.

Explainable-AI(XAI) offers great benefits to identify and classify of potato diseases, ranging from making AI models more interpretable and reliable to more trustworthy decisions for farmers and agronomists. This is vitally important in an agricultural environment where AI-driven decisions have a direct influence on crop condition and yield. Besides, XAI enables the debugging and improvement of a model by pointing out which areas of an image or features most affect its predictions, therefore allowing developers to find errors, bias, or overfitting. It allows for accurate localization of the disease by showing infected regions on the leaves to facilitate correct diagnosis and timely treatment.

Moreover, XAI renders model predictions interpretable even by non-expert users, fostering greater adoption of AI tools among farming communities. For researchers, it provides a view into nuanced patterns in symptoms and relationships which are not necessarily obvious, opening up new avenues for scientific inquiry. On the regulatory and ethical dimensions, XAI aids accountability and compliance since explainable outputs will be necessary to ensure the needed transparency in automated systems. All in all, the incorporation of XAI into potato disease classification systems serves not only to enhance model usability and performance but also trust in AI-powered agriculture.

### **1.1 Related Work**

Recent progresses in deep learning have improved the performance of plant disease detection and classification tasks. Several architectures have been developed to improve feature learning, reduce computation costs, and enhance generalization. A CNN architecture is used in [1] to develop a disease identification system within a number of crops based on leaf images. Multiple convolutional and pooling layers were used for optimal features extraction while training the model on a large dataset containing

diseased and healthy leaves. The authors emphasized enhancing the performance of the classifier by fine-tuning the network parameters. In [4], artificial intelligence techniques particularly deep learning is used to find early blight in potato crops. The deep learning framework was trained to detect symptoms of disease from complex image patterns within the remote sensed data. Their work illustrates the strength of merging AI with geospatial tools for early intervention in crop disease management. In [6], author introduces VGGNet, a deep-cnn model with hallmarks of small (3\*3) convolutional filters and extremely deep layers. VGGNet proved that deeper networks can be used to enhance performance in massive scale image recognition tasks such as ImageNet. It became the benchmark for simple yet powerful CNNs. In the field of deep learning, VGGNet was widely used as a benchmark in image classification. Res-Net, a deep convolution network using residual learning to overcome breakdown issues in deep learning models. The model is presented in [7]. Res-Net encourages gradient flow during training. Res-Net increases accuracy in image recognition by making it feasible to train deep learning models with over 100 layers. In [8], authors present 'MobileNetV2,' a deep network model adept in both embedded vision and mobile vision domains. Inverted residuals boost deep learning model performance with portability benefits. MobileNet V2 is adept at achieving a balance in model accuracy and computation complexity. Frequent usage can be found in resource-constrained devices such as IOT devices, smartphones. Deep model with 'hardware efficiency' is presented in this paper and optimized for 'real time embedded systems' in [9]. The main deep learning algorithms and architectures are reviewed in [10], along with an explanation of the functions and applications of models such as CNNs, RNNs, and autoencoders. It also covers performance patterns, present difficulties, and potential avenues for deep learning research. The deep learning techniques for plant disease detection and classification are compiled in [11] review, with an emphasis on CNN-based models and picture datasets. It demonstrates how well they work to increase automation and accuracy in agricultural disease diagnosis. Higher performance can be achieved compared to Squeeze Net without extra model complexity. Higher performance in resource-constrained devices can be guaranteed using this hardware model. To identify 'leaf diseases' without referring to a large dataset requirement, a self-supervised 'clustering algorithm' is presented in this work [12]. In [13], author examines the benefits and drawbacks of several imaging modalities, including visible, infrared, and hyperspectral imaging, for the identification of plant diseases in agriculture. The model utilizes a 'clustering algorithm' to classify a related set of diseases based on the application of 'representation learning,' which extracts relevant information from a set of 'unlabeled images.' A 'deep learning hybrid model' in [14] proposes digital image processing algorithms for 'potato diseases' identification and diagnostic purposes. To utilize collective capabilities and enhance 'accuracy in classification,' the model integrates different deep learning algorithms. 'Feature extraction,' 'image pre-processing algorithms' are used in this research to improve 'image pre-processing accuracy.' In contrast to conventional techniques, the study provides a deep learning-based method for classifying potato leaf diseases, demonstrating how AI models increase accuracy and efficiency [15]. In [16], work focuses on utilizing graph cut-based image segmentation to effectively separate and recognize disease regions in order to detect early and late blight in potato leaves. For the categorization of potato leaf disease, the authors suggest a CNN-based deep learning model, which shows excellent accuracy and resilience in automated disease detection [17]. In [18], a 'CNN model' is used for identifying 'potato leaf diseases.' Deep learning technique is used for 'potato leaves identification and diseases' with an objective to identify different diseases with higher accuracy using model 'training with a dataset of disease and healthy leaves. In order to assist early and accurate diagnosis, paper [19] uses deep learning approaches to categorize several potato leaf diseases,

demonstrating that CNN models can reliably detect and differentiate disorders.' A 'moderate accuracy and higher efficiency' in identifying different diseases is achieved using this proposed model. A 'hybrid deep learning model' used for 'potato leaves diseases' predictions increases 'features' and 'classification accuracy' by using a combination of deep learning models in [20]. In [21], it is shown that AI-based models can precisely identify disease patterns at the field size for precision agriculture by using artificial intelligence and remote sensing imagery to detect early blight disease in potato crops. It does not require any sort of manual pre-processing as it processes raw photographs of leaves directly. The authors in [22] came up with a new CNN structure for plant disease diagnosis considering model efficiency and precision. Their architecture design featured convolutional layers with optimized settings toward extracting high-features and reducing overfitting. They have validated the model using various plant disease data, including potato, and scored high regarding its classification. In [23] author uses one-class classifiers and visual feature analysis to propose an automated leaf disease detection system that may be applied to many crop species. The method improves early disease identification across crops by successfully identifying diseased leaves when there is a lack of labeled data. For the classification of potato leaf disease, author suggests a CNN model based on hierarchical deep learning [24]. The technique is useful for differentiating between various potato leaf diseases because it increases identification accuracy by learning disease signs at several levels. In [25], the author has proposed LDSNet (Lightweight Dense-Scale Network) to detect corn leaf disease. The architecture combines the dense connectivity and multi-scale feature fusion to effectively extract the global and local features from the network. It is dedicated to low-resource devices where the precision is not compromised. Author identifies plant leaf diseases using CNN and transfer learning models, demonstrating that when datasets are scarce, pre-trained networks increase accuracy and shorten training times [26]. In order to classify plant leaf diseases, this review methodically examines machine learning and deep learning approaches. It finds that deep learning techniques are more accurate and robust than older methods [27]. By autonomously learning discriminative disease traits, the authors' deep CNN model achieves good performance in crop disease detection from leaf images [28]. In [29], author demonstrates efficient large-scale disease surveillance by using artificial intelligence and remote sensing data to identify early blight illness in potato crops.

In [30], the author applied deep transfer learning for identifying and classifying plant diseases among different species. They evaluated different pre-trained architectures, which include VGG, ResNet, and Mobile-Net. They achieved high accuracy despite working with a smaller set of samples.

## **1.2 Motivation**

The main justification for using XAI in potato disease detection and classification is for enhanced trust, transparency, and interpretability of agriculture-based deep learning models. Although the classical black-box models are accurate, they are not transparent in their decision-making process, which is very important for farmers, agronomists, and other interested parties who rely on a correct diagnosis for effective management of crops. Using XAI techniques like SHAP or LIME, one could determine which features of the image of the leaf drive the model predictions and would assist with decision verification, identification of bias, and guiding improvements to model development and disease control. This is particularly important in sensitive sectors like agriculture, where bad predictions can result in economic loss or overuse of treatments.

### 1.3 Research Contribution

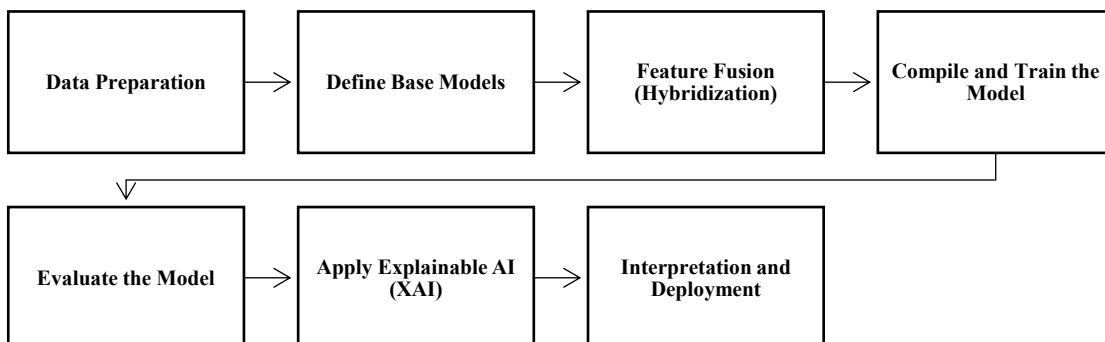
Explainable AI algorithms like Grad-Cam, Lime and Shap can be used for better performance. How XAI will be beneficial for research explained as follows-

- **Improved Model Transparency-** The study bridges the gap between high-performance deep learning models and interpretability through the use of XAI methods to visually and explainable reason how decisions are arrived at so that the predictions made are comprehensible to domain experts.
- **Trust and Adoption in Farming-** The work by making disease classification models interpretable creates trust among farmers and agricultural experts and hence encourages broader adoption and deployment in actual farming.
- **Detection of Bias and Model Flaws-** XAI helps in detecting potential biases or flaws in the model predictions, for instance, misclassifications because of comparable visual attributes among diseases, and allows for specific improvement in model training and balancing of datasets.
- **Domain-Relevant Feature Insights-** Biological relevance is contributed to by the research, which correlates model explanations with apparent disease symptoms to help agronomists verify AI results using their expert knowledge.
- **Basis for Decision Support Systems-** The study lays the foundation for developing explainable and trusted AI-based decision support systems in precision agriculture that could be further extended to other crops and plant disease detection contexts.

## 2. Proposed Approach

Such a combination of two models, Lightweight CNN and NASNet, makes use of the best of both architectures for effective detection and classification potato plant diseases. The Lightweight CNN is implemented in order to keep the computational complexity as low as possible, hence making the model effective to deploy in real-time and edge-device applications for the agricultural domain. However, NASNet brings its strong feature extraction abilities, inherited from neural architecture search, to the table and reinforces the model with better learning of sophisticated visual patterns across different disease groups. This results in better performance with respect to the classification of diseases and still allows the model to remain concise and deployable.

This critical layer of interpretability is achieved by combining the hybrid model with Explainable AI approaches like Grad-Cam or LIME as given in Figure 1. XAI helps in highlighting areas of an input image most determinative in the model's output, thereby enabling a farmer, agronomist, or researcher to understand why a classification was made. The transparency not only helps build trust in the results of the model but also helps diagnose errors or bias in the learning process of the model. Finally, a hybrid framework able to implement XAI increases the value and accountability of AI-driven plant disease diagnosis within the realm of precision agriculture.



### Figure 1- Hybrid model with Explainable-AI

**Algorithm:** Hybrid Feature-Fusion Model with Explainable AI

**Input:** Raw dataset D

**Output:** Trained hybrid model  $M^*$  and explanation results  $XAI\_R$

#### Step 1: Data Preparation

Pre-processing starts with importing the raw dataset D, after which data cleaning is carried out, missing values are handled, and normalization or standardization techniques are applied. After pre-processing, data is break into training and testing subsets.

#### Step 2: Define Base Models

Base learning models is chosen and then initialized. These models, referred to as  $\{B_1, B_2, \dots, B_n\}$  are utilized to form the basis for generating various feature representations.

#### Step 3: Feature Fusion (Hybridization)

Each base model extracts its feature representation from the training data. The resulting sets of features are then combined by a fusion strategy, such as concatenation or weighted fusion, into one unified hybrid feature space.

#### Step 4: Compile and Train the Model

With the help of these blended features, a hybrid learning model  $M$  can be developed. A suitable loss function and an optimization algorithm can be used, which will train model on the training dataset to reach an optimized model  $M^*$ .

#### Step 5: Model Evaluation

Accuracy, Precision, Recall, F1-score are basic performance measures used to check the performance of model on the test dataset for predictive purposes.

#### Step 6: Apply Explainable AI (XAI)

XAI techniques such as LIME and Grad-CAM can be used to understand the predictions of a model. They are used to create visual or numeric explanations based on the degree to which each of the input variables affects an output.

#### Step 7: Interpretation and Deployment

Outputs from XAI are examined to understand and validate the behaviour of the model. Finally, the model is put to practical usage with the help of information gained from analysis.

### Methodology

#### 2.1 Dataset Acquisition

Data utilized here were gathered from Kaggle, titled "Potato Plant Diseases." It includes 3,076 labelled images of potato plant leaves, both healthy and diseased, which have been carefully selected to provide identification and classification of different diseases of the potato crop. The data are free and intended for use on an academic and research basis. It consists of a number of classes that represents various types of diseases, as explained in Table 1.

**Table 1: Summary of Potato Dataset**

| Classes     | Number of Images |
|-------------|------------------|
| Fungi       | 748              |
| Late-Blight | 1000             |
| Pest        | 611              |
| Bacteria    | 569              |
| Healthy     | 201              |

|              |      |
|--------------|------|
| Nematode     | 68   |
| Virus        | 532  |
| Early-Blight | 1000 |

The images are provided in JPEG or PNG formats with resolutions typically ranging from  $1200 \times 1200$  to  $1500 \times 1500$  pixels.

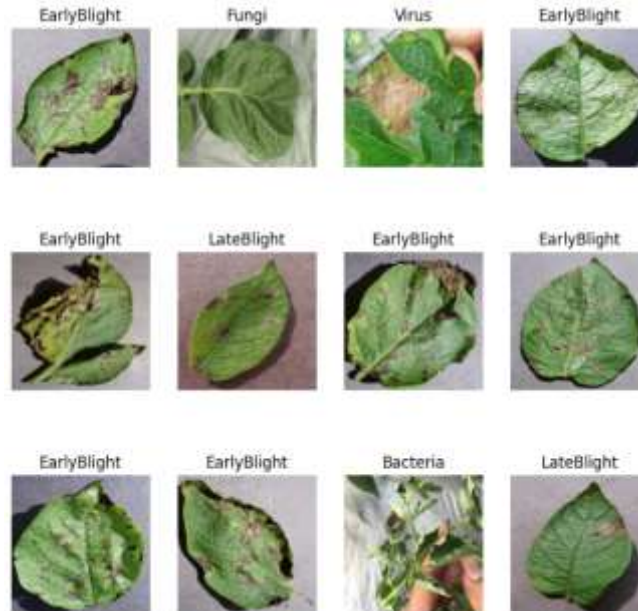


**Figure 2** *Samples of potato leaf diseases*

Figure 2. illustrates various types of diseases in the leaves of plants, which are identified as Bacteria, Virus, Fungi, and Potato Early Blight. Every picture clearly shows specific symptoms-spots or color that can visually help discrimination among the classes of diseases.

### 3.2 Pre-processing

Pre-processing is a very important step when working with Deep Convolutional Neural Networks, since it provides better feature extraction and reduces computational loads, hence enhance the overall performance of model. Most crucial steps for pre-processing are image resizing, image normalization, and data augmentation. Image resizing makes all input images the same size, such as  $128 \times 128 \times 3$ , to match the CNN input layer and keep the dataset uniform. Normalization normalizes the pixel values in a specific domain, for instance, between  $[0,1]$  or  $[-1,1]$ ; this stabilizes the training and hastens convergence. To synthetically grow the dataset, data augmentation is performed using flipping, zooming, brightness adjustment, and rotation to improve model generalization and reduce the risk of overfitting.

### 3.3 Classification with Convolutional Layers

The convolutional layer in a deep CNN searches for spatial features such as edges, textures, and other information in an input feature map using a set of learned filters or kernels. As part of the computations in this step, where each filter traverses an input with a definite stride to obtain an output activation map, a dot product computation in its receptive field among input elements and filter weights is conducted. Filter size, stride, and padding can be adjusted to modulate spatial dimensions to define specific sizes of output feature maps for convolution layers. Deeper layers learn increasingly abstract

representations; hence, by increasing filter numbers, different specialized features can be detected.

### 3.3.1 Convolutional Layer

Important part of convolution neural network is a convolutional layer, that is able to extract features from the image automatically. Various learnable filters (kernels) slides over the input to detect features, edges, textures, and higher-level structures in deeper layers. The operation of convolution at point (i,j) is defined:

$$Y(i,j) = \sum_m \sum_n X(i+m, j+n) \cdot K(m,n) \quad (1)$$

Let X be the input feature map, K be a kernel of size  $m \times n$  and Y is an output feature map. Output feature map can be calculated as:

$$O = \lfloor (I - K + 2P)/S \rfloor + 1 \quad (2)$$

where O is the dimension of the output, I for the dimension of the input, K is the size of the kernel, P the padding, and S is the stride.

### 3.3.2 Max Pooling Layer

It performs down-sampling by segmenting the input into non-overlapping or overlapping regions and taking the maximum value within each region:

$$Y(i,j) = \max\{(m,n) \in R(i,j)\} X(m,n) \quad (3)$$

This operation reduces spatial dimensions and computational cost, alleviates overfitting, preserves the most salient features, and increases translation invariance.

### 3.2.3 Fully Connected (Dense) Layer

A fully-connected layer connects each neuron to every neuron of the previous layer. It combines high-level features extracted by the earlier layers and then maps them onto the final output classes:

$$Y = f(WX + B) \quad (4)$$

where W represents the weight matrix; X, the input vector; B, the bias vector; and f() is a nonlinear activation function, for instance ReLU.

### 3.2.4 Parameter Calculation in Convolutional Layers

The total number of trainable parameters in a convolutional layer is computed as:

$$\text{Parameters} = (K_h \times K_w \times C_{in} + 1) \times C_{out} \quad (5)$$

where  $K_h \times K_w$  is the spatial size of the kernel,  $C_{in}$  is the number of input channels,  $C_{out}$  is the number of output channels (filters), and the "+1" accounts for the bias term of each filter.

## 3.4 Performance Evaluation Metrics

Below are standard classification metrics derived from the confusion matrix, which were used to evaluate the model's performance-

Accuracy is the Proportion of correctly classified instances.

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN) \times 100\% \quad (6)$$

$$\text{Error Rate} = 1 - \text{Accuracy} \quad (7)$$

Precision is defined as the ratio of correctly predicted positive instances to all instances that have been predicted as positive.

$$\text{Precision} = TP/(TP + FP) \times 100\% \quad (8)$$

Recall (Sensitivity) is the ratio of correctly predicted positive instances to all actual positive instances.

$$\text{Recall} = TP/(TP + FN) \times 100\% \quad (9)$$

F1-score is harmonic mean of precision and recall; especially useful for imbalanced datasets.

$$\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (10)$$

Where TP is True Positive, TN stands for True Negative, FP is False Positive and FN for False Negative.

### 3.5 Result of Experiment

This log shows the metric of validation and training, depicting the performance of a XAI based hybrid deep CNN model during 80 epochs.

**Table 2: Report of Classification**

| Class        | Precision | Recall | F1-Score | Support |
|--------------|-----------|--------|----------|---------|
| Bacteria     | 0.98      | 0.98   | 0.98     | 570     |
| EarlyBlight  | 1.00      | 1.00   | 1.00     | 1015    |
| Fungi        | 0.89      | 0.97   | 0.93     | 749     |
| Healthy      | 0.95      | 0.84   | 0.89     | 202     |
| LateBlight   | 1.00      | 1.00   | 1.00     | 1005    |
| Nematode     | 1.00      | 0.70   | 0.82     | 69      |
| Pest         | 0.95      | 0.79   | 0.87     | 611     |
| Phytophthora | 0.92      | 0.97   | 0.94     | 347     |
| Virus        | 0.87      | 0.98   | 0.92     | 534     |
| Accuracy     |           |        | 0.96     | 5102    |
| Macro Avg    | 0.95      | 0.91   | 0.93     | 5102    |
| Weighted Avg | 0.96      | 0.95   | 0.95     | 5102    |

From classification report, the hybrid model reached a good performance overall, with 96% accuracy, 0.93 macro average F1-score, and 0.95 weighted average F1score. This could support the fact that it succeeded in multi-classifying the diseases of potato leaves. In fact, it had perfect precision, recall, and F1score for Early-Blight and Late-Blight, showing it is very good at identifying these diseases. For Virus and Fungi, it has very high recalls but a bit lower precision, which indicates some tendency toward false positives. Its accuracy on the class Nematode is poor, though, with a recall of 0.70 but with perfect precision probably because of small sample size. Compared to Healthy leaves, the model has high precision of 0.95 but a lower recall of 0.84, indicating the occasional misclassification of the healthy samples as diseased. The model is generally reliable but perhaps would benefit from better recall on underrepresented or visually indistinguishable classes.

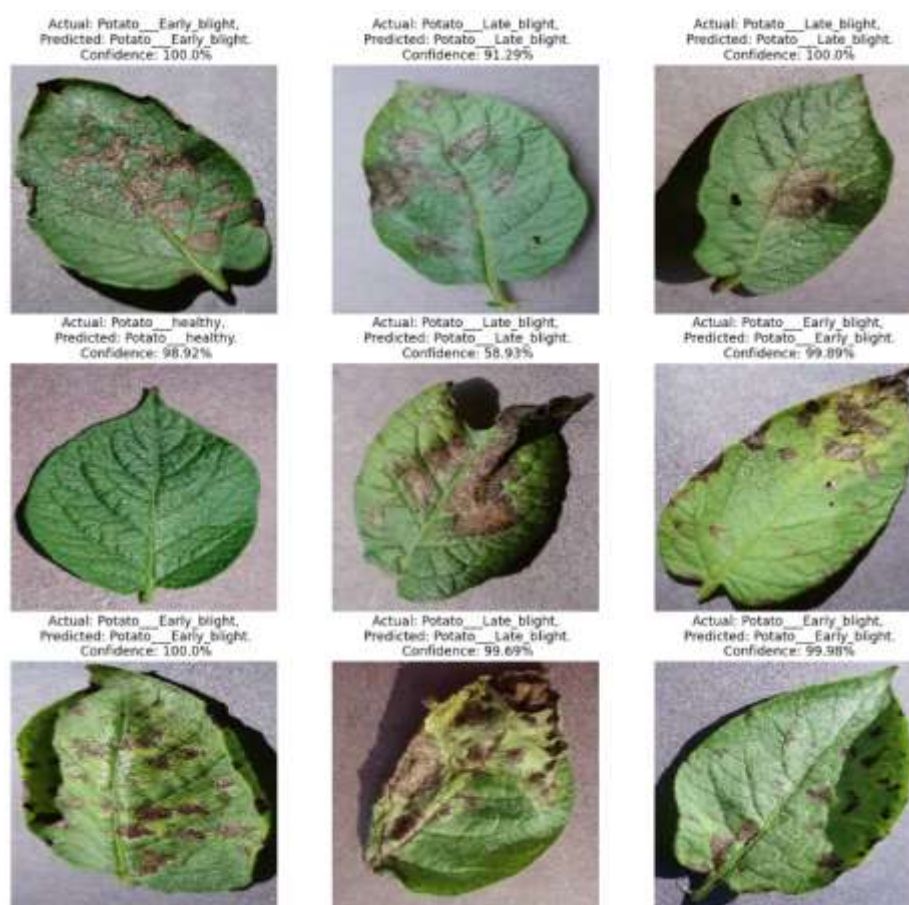


**Figure 3- Actual Disease, Predicted Disease and Confidence**

Figure 3. presents several potato leaf samples along with the classification result from the hybrid model, including the ground truth disease label, the predicted label, and the confidence score of the prediction. The images here show that the model was able to identify the actual disease label for healthy leaves and those suffering from early and late blight, with very high confidence in most cases, often exceeding 99%. Even for samples with complex or overlapping lesion patterns, the model consistently identified the correct disease category, with only one case of moderately lower confidence (58.93%) in the case of late blight, which may indicate slight uncertainty due to subtle or ambiguous symptoms. Overall, this figure demonstrates the high reliability and robustness of the model under real-world disease identification across diverse leaf appearances.

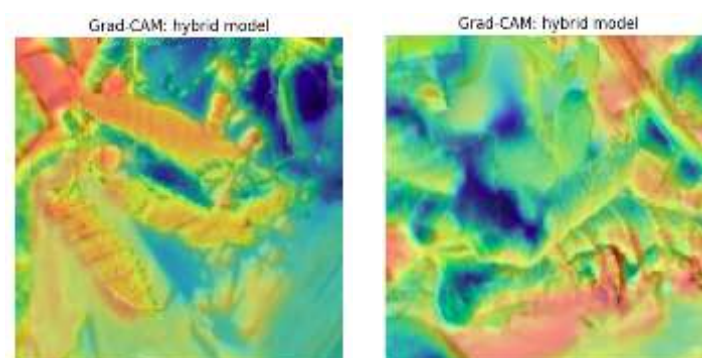


**Figure 4: Grad-Cam implementation on Hybrid -Model**

These Grad-CAM heatmaps highlight the regions of the potato leaf images on which the hybrid model relied the most in making a disease prediction as given in figure 4. Red and yellow represent strong attention from the model, indicating that these regions contributed most to the classification, while green indicates moderate importance, and blue reflects little or no influence. In both images, the model places most of its focus on specific leaf textures, vein structures, and surface irregularities, suggesting it has learned to detect visual symptoms such as lesions, discoloration, and deformation rather than random background regions. This serves to indicate that the hybrid architecture makes biologically meaningful decisions by localizing disease-relevant features onto the leaf surface.

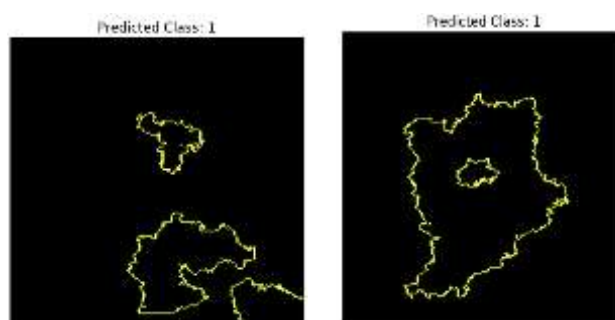


**Figure 5: Lime implementation on diseased leaves**

In figure 5. both images shown here are LIME visualizations for the region's most responsible for the model's prediction for class 1. The yellow outlines in both images are super pixels or local segments that LIME has singled out as carrying a high degree of positive responsibility for the predicted class. Two distinct regions are drawn in the first image, which means the model used a prediction based on several isolated regions, possibly disease symptoms spread out within the input. This infers that the model is sensitive to distributed features spatially. On the contrary, the second image presents a single larger and more compact area with well-defined edges and a central void, indicating that the model's decision was made based on a dense lesion-like structure. LIME provides transparency to the model's internal decision-making by visually illustrating the portion of the input image that contributed to the classification. This not only confirms that the model is paying attention to patterns that are relevant-e.g., areas of disease infection-but also builds confidence in its predictions by anchoring those to human-observable attributes, making it an essential component in explainable AI for plant disease diagnosis.

### **3. Comparison and discussion**

Performance of the proposed hybrid model, Lightweight CNN + NASNet, is outstanding, with an accuracy of 96% showing strong generalization and high F1-scores on different disease classes. Compared to other models, this significantly outperforms a single CNN, which has approximately 88-90% accuracy but performs poorly in intricate and fine-grained features, though simpler and faster to train as explained in Table 3. ResNet50 is a bit better, with 92-93% accuracy attributed to deeper architecture and reuse of features, but is accompanied by higher computational requirements, hence not so suitable for mobile or real-time applications. VGG16 has a rough accuracy of 90-91% and is good on moderate datasets; however, its heavy design causes overfitting on small datasets. Mobile-Net, which is built for efficiency, offers 91-92% accuracy, marginally poorer on minority classes. Efficient-Net provides a balanced accuracy of 93-94% with an

acceptable trade-off between performance and efficiency but is still just short of the hybrid model's F1-macro. Generally, the hybrid model provides the most optimal balance between accuracy, generalization, and interpretability, particularly for heterogeneous disease detection in agricultural environments as given in figure 6.

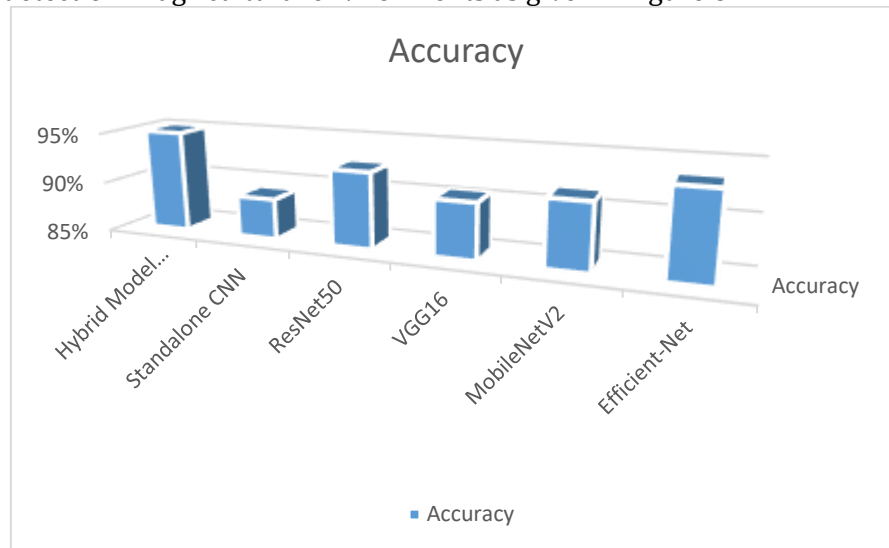


**Figure 6: Accuracy comparison to other models**

**Table 3: Report of Comparison**

| Model                                   | Accuracy | Strengths                                        | Limitations                                                     |
|-----------------------------------------|----------|--------------------------------------------------|-----------------------------------------------------------------|
| Hybrid Model (Lightweight CNN + NASNet) | 96%      | High F1-scores, generalizes well across classes. | Slight drop in recall for minority classes like Nematode.       |
| Standalone CNN                          | 88-90%   | Simpler, faster training.                        | Struggles with complex or fine-grained features.                |
| ResNet50                                | 92-93%   | Good depth and feature reuse.                    | Higher computational cost, less suitable for mobile deployment. |
| VGG16                                   | 90-91%   | Performs decently on moderate-size datasets.     | Heavier model, over fits on small data.                         |
| MobileNetV2                             | 91-92%   | Lightweight and efficient.                       | Slightly lower accuracy on minority classes.                    |
| Efficient-Net                           | 93-94%   | Optimized accuracy-efficiency trade-off.         | Still marginally lower than hybrid's F1-Score.                  |

#### **4. Conclusion**

The proposed hybrid model comprising Lightweight CNN and NASNet performs better in the classification of potato leaf diseases, achieving accuracy of 96% with high F1-scores for all categories. This is quite outstanding compared to other models such as stand-alone CNNs, which have 88-90% accuracy, ResNet50 and its variants with 92-93% accuracy, VGG16 with 90-91%, and MobileNetV2 with an accuracy of 91-92%. It offers a good trade-off between computational cost and accuracy. Even when compared to EfficientNetB0, which gave 93-94% accuracy, the macro F1-score is higher for the hybrid model. This means it outperforms both dominant and minority disease classes. Explainable AI methods have been applied, including LIME and Grad-CAM, to further enhance the credibility of the model. First, LIME visualizations picked out the individual areas that are affecting the predictions, hence showing that the model's attention was on relevant disease-affected regions. Grad-CAM outputs showed that NASNet focuses on specific lesion areas with high confidence, while Lightweight CNN reflects more general attention. An amalgamation that guarantees accuracy and efficiency is assured by this. The explainability offered by the techniques enhances the reliability of the model choices, something quite vital in real-world agricultural use. In conclusion, the hybrid model is an efficient, interpretable, and comprehensive solution for plant disease diagnosis. This is the perfect application of the hybrid model, in which both accuracy and interpretability should be of utmost importance.

#### **References: -**

- [1] Y. Kurmi, P. Saxena, B.S. Kirar, S. Gangwar, V. Chaurasia, A. Goel, Deep CNN model for crops' diseases detection using leaf images, *Multidim. Syst. Sign. Process.* 33 (2022) 981–1000, doi: 10.1007/s11045-022-00820-4
- [2] S. Mishra, R. Sachan, D. Rajpal, Deep convolutional neural network based detection system for real-time corn plant disease recognition, *Procedia Comput. Sci.* 167 (2020) 2003–2010, doi: 10.1016/j.procs.2020.03.236
- [3] Fatema Tuj Johora Faria, Mukaffi Bin Moin, Ahmed Al Wase, Md. Rabiul Sani, Khan Md Hasib, and Mohammad Shafiul Alam. Classification of potato disease with digital image processing technique: A hybrid deep learning framework. In 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC), pages 0820–0826, 2023, doi: 10.1109/CCWC57344.2023.10099162
- [4] H. Afzaal, A.A. Farooque, A.W. Schumann, N. Hussain, A. McKenzie-Gopsill, T. Esau, et al., Detection of a potato disease (early blight) using artificial intelligence, *Remote Sens. (Basel)* 13 (2021) 411, doi: 10.3390/rs13030411
- [5] R. Mahum, H. Munir, Z.-U.-N. Mughal, M. Awais, F. Sher Khan, M. Saqlain, et al., "A novel framework for potato leaf disease detection using an efficient deep learning model," *Human and Ecological Risk Assessment: an, Int. J.* (2022) 1–24, doi: 10.1080/10807039.2022.2064814
- [6] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition", in *Proc. 3rd Int. Conf. Learn. Represent. (ICLR)*, San Diego, CA, USA, 2015, doi.org/10.48550/arXiv.1409.1556
- [7] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition", in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 770778, doi.org/10.1109/CVPR.2016.90
- [8] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted residuals and linear bottlenecks", in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 45104520, doi.org/10.1109/CVPR.2018.00474

- [9] A. Gholami, K. Kwon, B. Wu, Z. Tai, X. Yue, P. Jin, S. Zhao, and K. Keutzer, "SqueezeNext: Hardware-aware neural network design", in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW), Jun. 2018, doi.org/10.1109/CVPRW.2018.00215
- [10] A. Shrestha and A. Mahmood, "Review of deep learning algorithms and architectures," IEEE Access, vol. 7, pp. 53040–53065, 2019, doi.org/10.1109/ACCESS.2019.2912200
- [11] L.Li, S. Zhang, and B.Wang, 'Plant disease detection and classification by deep learning—A review," IEEE Access, vol. 9, 2021,doi.org/10.1109/ACCESS.2021.3069646
- [12] M.M.Monowar, M.A.Hamid, F. A. Kateb, A. Q. Ohi, and M. F. Mridha, "Self-supervised clustering for leaf disease identification," Agriculture, vol. 12, no. 6, p. 814, Jun. 2022, doi.org/10.3390/agriculture12060814
- [13] V. Singh, N. Sharma, and S. Singh, "A review of imaging techniques for plant disease detection," Artif. Intell. Agricult., vol. 4, Jan. 2020, doi.org/10.1016/j.aiia.2020.10.002
- [14] Fatema Tuj Johora Faria, Mukaffi Bin Moin, Ahmed Al Wase, Md. Rabius Sani, Khan Md Hasib, and Mohammad Shafiul Alam," Classification of potato disease with digital image processing technique: A hybrid deep learning framework", in 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC),doi.org/10.1109/CCWC57344.2023.10099162
- [15] Nour Eldeen Khalifa, Mohamed Taha, Lobna Abou El-Magd, and Aboul Ella Hassanien," Artificial Intelligence in Potato Leaf Disease Classification: A Deep Learning Approach", 2021, doi.org/10.1007/978-3-030-59338-4\_4
- [16] Chaojun Hou, Jiajun Zhuang, Yu Tang, Yong He, Aimin Miao, Huasheng Huang, and Shaoming Luo, "Recognition of early blight and late blight diseases on potato leaves based on graph cut segmentation", Journal of Agriculture and Food Research, 5:100154,2021,doi.org/10.1016/j.jafr.2021.100154
- [17] Utkarsh Yashwant Tambe, A. Shobanadevi, A. Shanthini, and Hsiu-Chun Hsu," Potato leaf disease classification using deep learning: A convolutional neural network approach", 2023, doi: 10.13052/rp-9788770040723.043
- [18] Hritwik Ghosh, Irfan Rahat, Kareemulla Shaik, Syed Khasim, and Manava Yesubabu," Potato leaf disease recognition and prediction using convolutional neural networks", ICST Transactions on Scalable Information Systems, 2023, doi.org/10.13052/rp-9788770040723.043
- [19] Md Ashraful Islam and Md Sikder. Hanif, "A Deep Learning Approach to Classify the Potato Leaf Disease", (June 15, 37(12):143–155, 2022, doi: 10.9734/JAMCS/2022/V37I121735
- [20] Fizzah Arshad, Muhammad Mateen, Shaukat Hayat, Maryam Wardah, Zaid Al-Huda, Yeong Gu, and Mugahed A. Al-antari Aisslab, "Pldpnet: End-to-end hybrid deep learning framework for potato leaf disease prediction", Alexandria Engineering Journal, 78:406–418, 08 2023, doi: 10.1016/j.aej.2023.07.076
- [21] H. Afzaal, A.A. Farooque, A.W. Schumann, N. Hussain, A. McKenzie-Gopsill, T. Esau, et al., Detection of a potato disease (early blight) using artificial intelligence, Remote Sens. (Basel) 13 (2021) 411, doi: 10.3390/rs13030411
- [22] Sk Mahmudul Hassan, Arnab Kumar Maji," Plant Disease Identification Using a Novel Convolution Neural Network", January14, 2022, doi: 10.1109/ACCESS.2022.3141371.
- [23] Pantazi, X.; Moshou, D.; Tamouridou, A. Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers. Comput. Electron. Agric. 2019, 156, 96–104, doi: 10.1016/j.compag.2018.11.005

- [24] Kumar, A.; Patel, V.K. Classification and identification of disease in potato leaf using hierarchical based deep learning convolutional neural network. *Multimed. Tools Appl.* 2023, 82, 31101–31127, doi: 10.1007/s11042-023-14663-Z
- [25] W. Zeng, H. Li, G. Hu, and D. Liang, "Lightweight dense-scale network (LDSNet) for corn leaf disease identification," *Comput. Electron. Agricult.*, vol. 197, Jun. 2022, doi: 10.1016/j.compag.2022.106943
- [26] S. M. Hassan, A. K. Maji, M. Jasiński, Z. Leonowicz, and E. Jasińska, "Identification of plant-leaf diseases using CNN and transfer-learning approach," *Electronics*, vol. 10, Jun. 2021, doi: 10.3390/electronics10121388
- [27] R. Kumar, A. Chug, A. P. Singh, and D. Singh, "A systematic analysis of machine learning and deep learning based approaches for plant leaf disease classification: A review," *J. Sensors*, vol. 2022, Jul. 2022, doi: 10.1155/2022/3287561
- [28] Y. Kurmi, P. Saxena, B.S. Kirar, S. Gangwar, V. Chaurasia, A. Goel, Deep CNN model for crops' diseases detection using leaf images, *Multidim. Syst. Sign. Process.* 33 (2022) 981–1000, doi: 10.1007/s11045-022-00820-4
- [29] H. Afzaal, A.A. Farooque, A.W. Schumann, N. Hussain, A. McKenzie-Gopsill, T. Esau, et al., Detection of a potato disease (early blight) using artificial intelligence, *Remote Sens. (Basel)* 13 (2021) 411, doi: 10.3390/rs13030411
- [30] Bhanu Goyal, Anil Kumar Pandey, Rakesh Kumar, & Meenu Gupta (2023). "Disease Detection in Potato Leaves Using an Efficient Deep Learning Model." 2023, International Conference on Data Science and Network Security (ICDSNS), pp. 01–05, doi: 10.1109/ICDSNS58469.2023.10245369.