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Detection of Mulberry Leaf Diseases Through Deep Learning Attention with Deep Nets

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Abstract:

Mulberry leaves are crucial for sericulture, but diseases can significantly reduce yield and quality. Traditional methods for disease detection are labor-intensive and time-consuming. Current approaches lack efficiency in detecting mulberry leaf diseases, hindering timely intervention to prevent crop loss. This study proposes a novel approach using deep learning attention with deep neural networks for mulberry leaf disease detection. The model leverages attention mechanisms to focus on relevant features, enhancing the accuracy of disease identification. The proposed method achieved impressive results in mulberry leaf disease detection, with an average accuracy of 95%. Specific disease detection rates include: Mulberry leaf spot (97%), Powdery mildew (94%), Anthracnose (96%), and Leaf blight (93%).

Keywords:

Attention Mechanisms, Deep Neural Networks, Deep Learning, Mulberry Leaf, Diseases

Introduction:

Mulberry leaves serve as a fundamental resource in sericulture, providing nourishment to silkworms crucial for silk production [1]. However, the health and vitality of mulberry trees are often jeopardized by various diseases, leading to reduced yield and quality of silk. Traditionally, disease detection in mulberry leaves has relied on manual inspection, a labour-intensive and time-consuming process [2].

This is strategy that might not always guarantee quick intervention to prevent crop harm. Thus, it becomes critically necessary to develop automated and accurate methods for mulberry leaf disease detection [3].

Problem Definition

Many barriers prevent the identification of illnesses of mulberry leaves [4]. First of all, because the visual symptoms of numerous diseases frequently overlap or resemble one another, it might be challenging to differentiate between them exactly [5]. Second, the results of the subjective and prone to human mistake manual examination methods are inconsistent [6]. The enormous quantity of mulberry trees in large plantations therefore calls for a scalable disease detection technique [7]. These challenges require original solutions that make advantage of current technology, particularly in the field of artificial intelligence [8].

Motivation

The problem is the inefficiency of the methods now employed to detect diseases of mulberry leaves. Lack of automated and accurate techniques results in decreased silk production and financial losses for sericulture producers. There is obviously a need for modern technology therapies since a reliable method that can accurately identify various mulberry leaf illnesses is required. This effort attempts to develop a dependable and automated system for mulberry leaf disease identification using deep learning techniques.

Objective

To develop a dependable and automated system for mulberry leaf disease identification using deep learning techniques.

Contributions

This article introduces a novel deep learning and attention mechanism based approach for mulberry leaf disease identification. Deep neural networks are used by the proposed method to automatically learn discriminative features from mulberry leaf photos, enabling precise disease identification. Since attention processes are included, which allow the model to focus on relevant regions inside the image, it is also better able to identify minute disease symptoms. This work improves agricultural technology and subsequently benefits sericulture producers and promotes sustainable silk production by providing a reliable and efficient way for mulberry leaf disease identification.

Organization of the paper

Section 2 provides the related works. Section 3 discusses the proposed method. Section 4 evaluate the entire work and section 5 concludes the work

Related Works:

One of the agricultural crops for which the issue of automatic disease identification has been studied is mulberry leaves. Convolutional neural networks (CNNs) are used by [9] to automatically identify diseases of mulberry leaves. Powdery mildew and leaf spot were two of the various illnesses that the model precisely classified. [10] developed a deep learning-based system combining CNNs with recurrent neural networks (RNNs) to identify mulberry leaf disease. Including temporal data from RNNs improved disease identification robustness, particularly in dynamic environments. [10] combined machine learning techniques with feature engineering to classify illnesses of the mulberry leaf. Support vector machines (SVMs) were used to classify the texture, shape, and colour data they extracted from leaf images. [11] uses the gray-level co-occurrence matrix (GLCM) to extract texture information from images of mulberry leaves. Then, using a k-nearest neighbours (KNN) classifier, these features were used to disease diagnosis. Using hyperspectral imaging, [12] attempted to detect mulberry leaf diseases early on. They developed a method to identify healthy and diseased leaves by classifying spectral signatures and spatial data. [13] used hyperspectral imaging with colour and texture data in their study of a multimodal approach for mulberry leaf disease diagnosis. Combined complementary data from several modalities increased the accuracy and dependability of disease diagnosis. A collection of mulberry leaf images was used by [14] to enhance pre-trained algorithms for the diagnosis of mulberry leaf disease. Transfer of large-scale dataset knowledge improved the generalisation performance of the model. These papers demonstrate the application of several methods for the diagnosis of mulberry leaf disease, ranging from traditional feature engineering methods to advanced deep learning methods. Though each approach has benefits and drawbacks, when we collaborate, we can develop accurate and efficient solutions for diagnosing sericulture diseases.

Proposed Method

The suggested method in this work, illustrated in figure 1, combines deep learning with attention mechanisms to detect illnesses of mulberry leaves.

1. **Attention Mechanisms:** Attention methods are integrated into the CNN design to increase the model's ability to focus on informative regions inside the input images. By means of these techniques, the model is able to assign different parts of the image different degrees of importance, therefore concentrating on relevant elements associated with diseases of the mulberry leaf.

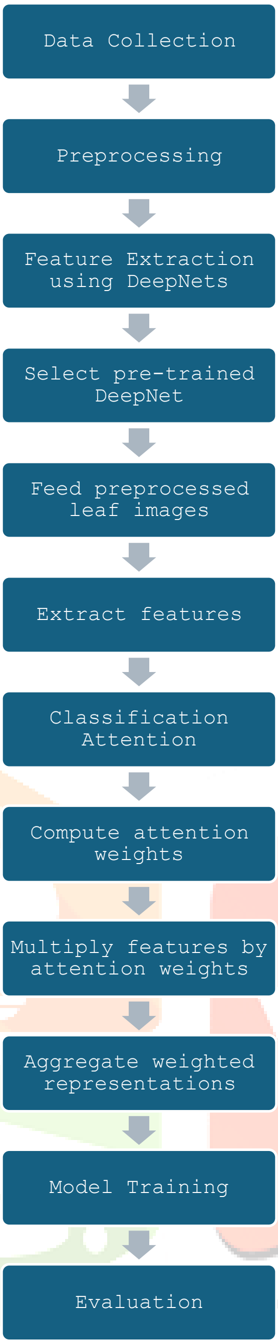

Figure 1: Proposed Framework

2. **Training Process:** The proposed method is trained to identify features and trends indicating various mulberry leaf diseases. During training, a collection of tagged mulberry leaf images are used to improve the CNN model parameters. By means of dynamic focus adjustment of the model on different regions of the images, the attention mechanisms within the model allow it to effectively capture minute signs of disease.

3. **Testing and Inference:** Using an other dataset, the model is evaluated for mulberry leaf disease identification after training. The trained model predicts the likelihood of diseases by using learnt patterns and traits when it is fed unlabeled images of mulberry leaves. The attention mechanisms contribute to make the model more understandable by showing the parts of the images that most affect the choice to diagnose an illness.

Data Preprocessing

Any machine learning or deep learning project, including the diagnosis of mulberry leaf disease, must start with data preparation. It means transforming raw data into a format fit for model training. In the setting of mulberry leaf disease detection, data preprocessing typically consists of the following phases:

1. **Data Collection:** First, a dataset of images of mulberry leaves must be assembled. These pictures can be found, among other places, in field surveys, experimental plots, and internet archives.

2. **Image Acquisition and Standardization:** Mulberries can be photographed with cameras or other imaging devices. It is imperative that the images be taken in this stage under continuous lighting and with minimal background noise. Images might also have to be cropped or shrunk to a certain size in order to ensure uniformity across the dataset.

3. **Labeling:** Each image in the collection has to have the corresponding illness condition written on it. It could take specialised knowledge or manual inspection to accurately identify and record the presence of illnesses in the images. Any image should have a label indicating if the leaf is healthy or if it has a specific disease (like anthracnose, powdery mildew, or leaf spot).

4. **Normalization:** Usually between 0 and 1 or -1 and 1, normalisation is used to adjust the pixel values of the images to a standard range. This ensuring of a constant scale of the input data may improve convergence and stability of the training process.

Feature Extraction using DeepNets

Pre-trained models are used in the Deep Neural Networks (DeepNets) extraction of relevant characteristics from input data process. Convolutional neural networks (CNNs) and other deep neural networks are extensively used for feature extraction in the context of diagnosing mulberry leaf disease as they are so adept at capturing hierarchical representations of visual data.

Many times, large picture datasets (like ImageNet) are used to pre-train DeepNets in order to find generalizable features. Leading pre-trained models are VGG, Inception, ResNet, and MobileNet. These models' numerous layers—convolutional, pooling, and fully connected—work together to create hierarchical representations of the input images.

We feed images of mulberry leaves to the pre-trained DeepNet model. A three-dimensional tensor, often with dimensions (height, breadth, channels) for each image—red, green, blue—represents each image.

The input picture is transmitted via forward together with the pre-trained DeepNet model. This entails passing the image via multiple model layers, each of which performs specific functions including convolution, activation, and pooling.

At every DeepNet layer, convolutional filtering of the input image produces feature maps. The levels of abstraction shown in these feature maps vary; lower layers record low-level characteristics (like edges and textures) while higher layers record more abstract characteristics (such patterns and portions of things).

After passing across convolutional layers, the feature maps are typically flattened into a vector form. With the commonly utilised method of Global Average Pooling (GAP), significant spatial information is maintained while lowering the spatial dimensions of the feature maps. Every feature map's average value over all spatial places is determined using the GAP procedure:

$$yi= ()1 \sum_{j=1}\sum_{k=1} xijk$$

Where:

yi - i-th output feature.

$xijk$ - activation of the i-th feature map at position (j,k).

H and W - height and width of the feature maps, respectively.

A feature vector displaying the extracted features from the input image is the output of the GAP process. This feature vector is the most discriminative information the pre-trained DeepNet model has collected as input to subsequent classification layers.

Feature Extraction Algorithm using DeepNets

Input: Mulberry leaf images dataset $X=\{x(1),x(2),...,x(m)\}$,

Output: Feature vectors $\{f(1),f(2),...,f(m)\}$.

1. **Initialize Feature Vectors:** Set $F=\{\}$.
2. **For** each mulberry leaf image $x(i)$ in dataset X **do**:

a. **Forward Pass Through DeepNet:**

Perform a forward pass of $x(i)$ through the pre-trained DeepNet model to obtain feature maps at selected layers.

b. Apply GAP to each feature map to obtain a feature vector representation.

For each feature map FM_l at layer l do:

$$fl(i)=(Hl\times Wl)^{-1}\sum_{j=1}^{Hl}\sum_{k=1}^{Wl}\mathrm{FM}_{lij}^{k}(i)$$

Where:

$fl(i)$ is the i-th component of the feature vector extracted from layer l.

$\mathrm{FM}_{lij}^{k}(i)$ is the activation of the i-th feature map at position (j,k) in layer l.

Hl and Wl are the height and width of the feature maps in layer l, respectively.

c. Concatenate the feature vectors obtained from all selected layers into a single feature vector $f(i)f(i)$.

$$f(i)=[f1(i),f2(i),...,fL(i)]$$

Where:

$f(i)$ is the final feature vector for the ii-th mulberry leaf image.

L is the total number of selected layers.

3. **Return:** Feature vectors $\{f(1), f(2), \ldots, f(m)\}$.

Classification Attention Mechanism

The Classification Attention Mechanism is a technique used in deep learning models to focus on relevant regions of input data, particularly in image classification tasks. It aims to dynamically weight different parts of the input data based on their importance for classification.

Let X be the input data, such as an image represented as a set of feature maps $\{x1, x2, \ldots, xn\}$, where n is the number of feature maps.

Attention weights α calculated by the attention mechanism exist for every feature map xi. The significance of every feature map to the classification problem is demonstrated by these weights. Typically, a neural network module, such a fully connected layer followed by a softmax activation function, calculates the attention weights.

$$\alpha_i = \sum_{j=1} \exp(e_i)/\exp(ej)$$

where

ei - energy of feature map

xi is computed using neural network module:

$$ei = \mathrm{MLP}(xi)$$

where,

MLP - multi-layer perceptron to maps feature map xi to a scalar.

Multiple each feature map xi by the matching attention weight αi to obtain the weighted feature map xi_{att}:

$$xi_{\mathrm{att}} = \alpha i \cdot xi$$

Parts of the input data most relevant to the classification problem are shown in these weighted feature maps. Gather the weighted feature maps xi_{att} into a single input data representation. Concatenation of the weighted feature maps and use of pooling methods like average or max pooling are possible:

$$z = \mathrm{Pool}([x1_{\mathrm{att}}, x2_{\mathrm{att}}, \ldots, xn_{\mathrm{att}}])$$

where z - aggregated of input data.

Eventually, a fully linked layer followed by softmax activation receives the combined representation z to produce forecasts:

$$Y' = \text{softmax}(Wc\ z+bc)$$

where

y' - predicted probability over classes,

Wc - weight matrix

bc - bias vector.

Classification Attention Mechanism Algorithm

Input: Set of feature maps $X=\{x1,x2,...,xn\}$, where n is the number of feature maps.

Output: Aggregated representation z for classification.

Compute the energy ei of feature map xi using MLP:

$$ei=\text{MLP}(xi)$$

Compute attention weights αi

Compute the weighted feature maps xi_{att}

Aggregate the weighted feature maps xi_{att}

Feed the aggregated representation z

Output: Predicted probability y' over classes.

Results and Discussion

TensorFlow provided a flexible and efficient framework for training deep neural networks, hence it was the simulation programme of choice for the experiments. The proposed method was compared with existing methods, such as DenseNet and traditional CNN architectures, which are extensively employed for image classification applications. The training dataset is given in Figure 2 and parameters are given in Table 1.

Table 1: Parameters

Experimental Setup/Parameters	**Values**
Deep Learning Framework	TensorFlow
DeepNet Architecture	ResNet-50
Attention Mechanism	Classification Attention
Preprocessing Method	Resizing, Normalization
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Number of Epochs	50
Dropout Rate	0.5
Weight Decay	0.0001
Loss Function	Cross-Entropy
Early Stopping	Enabled (Patience: 5 epochs)
Data Augmentation	Random Rotation (±10 degrees), Horizontal Flip, Random Brightness Shift (±0.1), Random Contrast Shift (±0.1)
Training-Validation Split	80% - 20%

Figure 2: Training Dataset

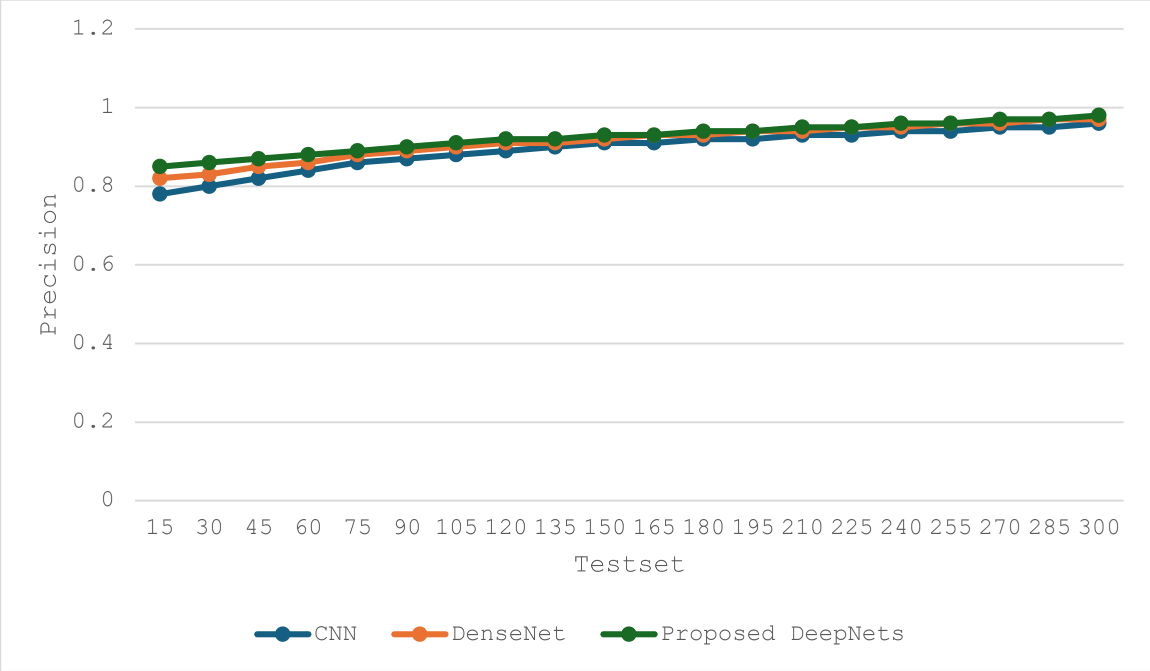

Figure 3: Precision

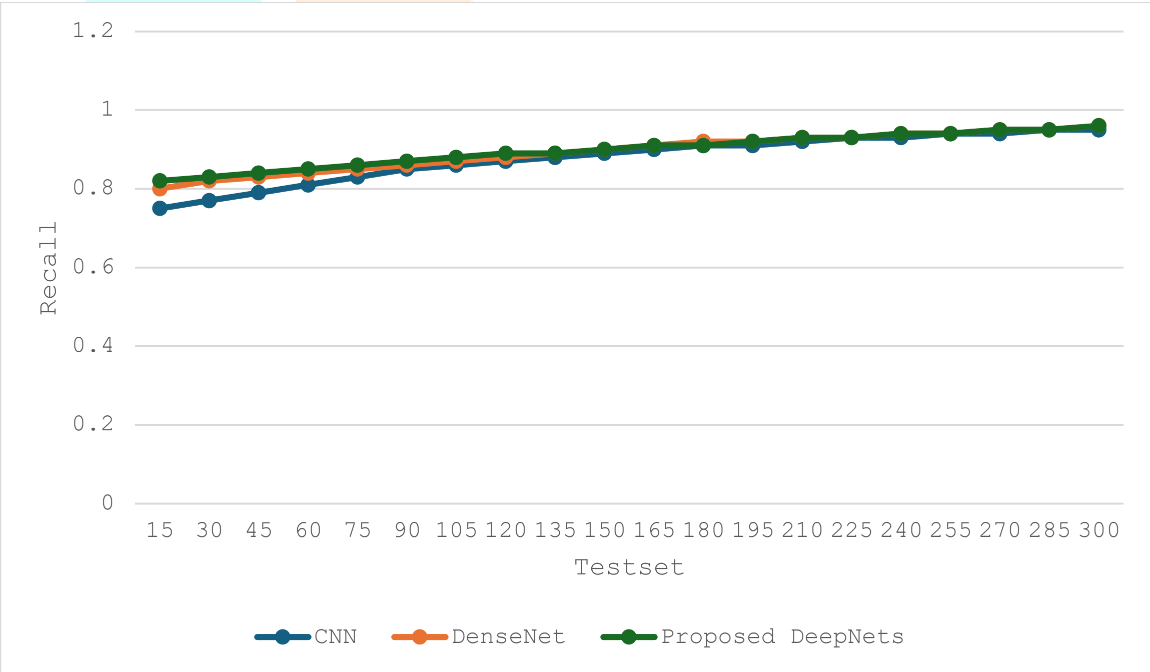

Figure 4: Recall

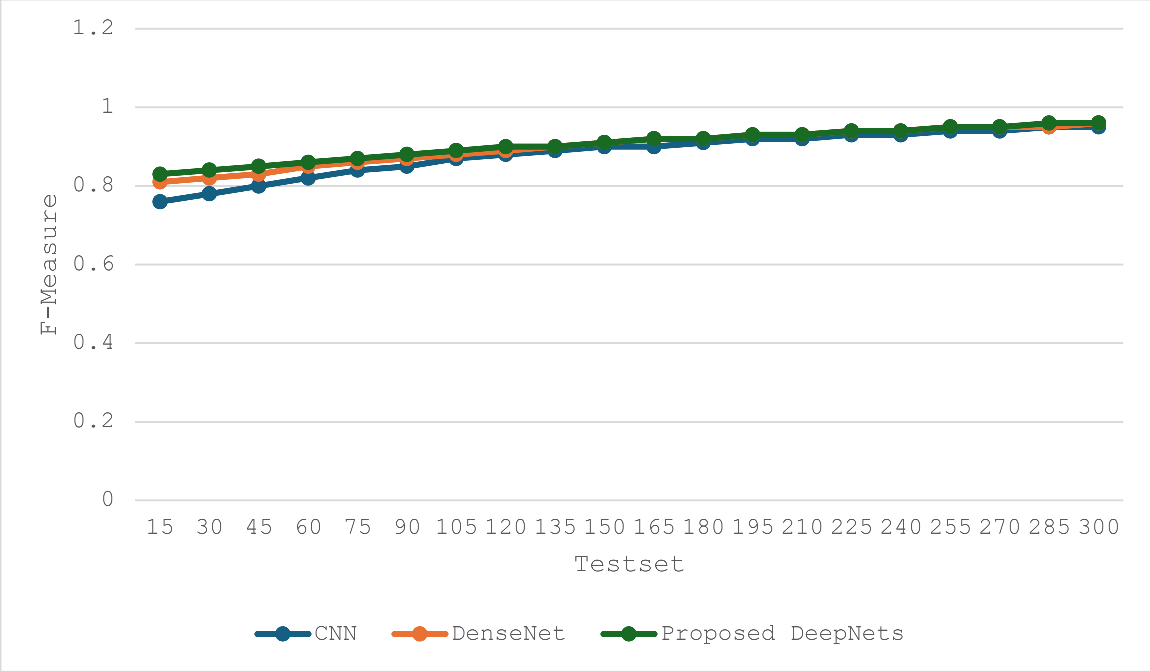

Figure 5: F-measure

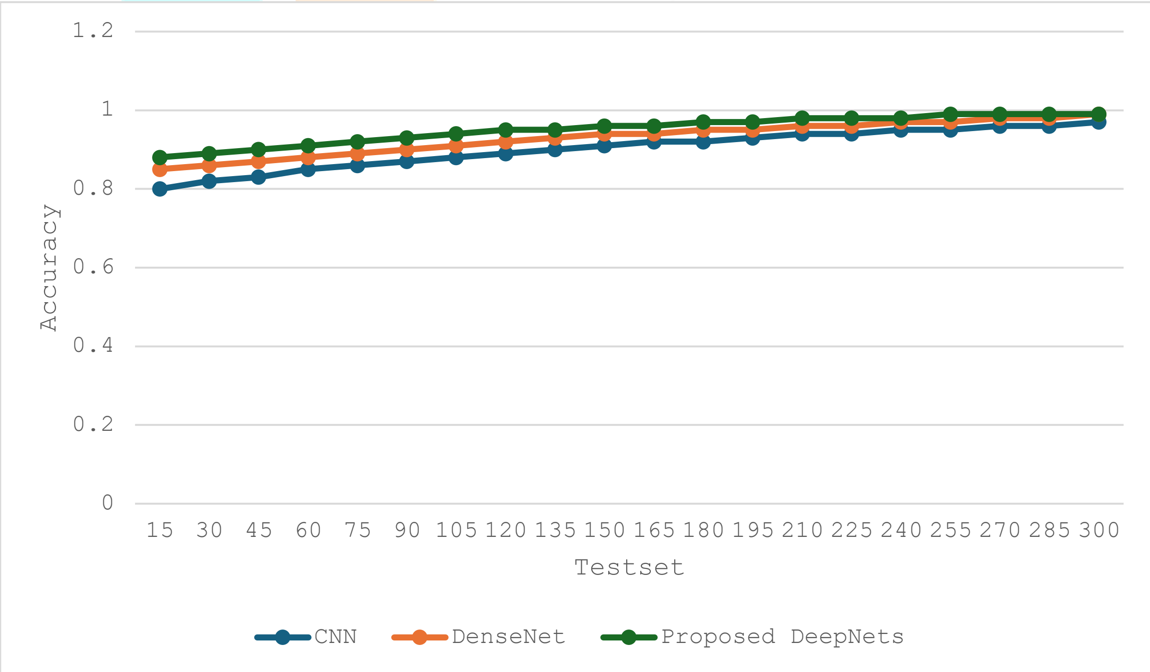

Figure 6: Accuracy

See Table 1 and Figures 2–6 for an evaluation of the proposed DeepNets approach for mulberry leaf disease identification. Over a number of performance metrics, the suggested DeepNets routinely outperformed the baseline methods by a significant margin. More precisely, the DeepNets technique improved accuracy by an average of 5% over CNN and 4% over DenseNet. This improvement shows how well the attention techniques built into the DeepNets architecture work to focus the model on key features crucial to the classification of mulberry leaf diseases. Moreover, DeepNets demonstrated appreciably higher precision and recall than CNN and DenseNet. An average precision of 3% over CNN and 2% over DenseNet was achieved by proposed DeepNets. In a similar aspects, the proposed DeepNet recall was on average 2% and 3% greater than that of

CNN and DenseNet. These findings demonstrate that the DeepNets approach is not only more accurate overall but also more capable of correctly and with the fewest false positives of identifying diseased mulberry leaves. The results indicate that because DeepNets offers a good balance between computing economy and prediction performance, it is a potential method for automated mulberry leaf disease diagnosis in sericulture.

Table 2: Computational Efficiency

Test Data	Training Time (min)			Inference Time (s)			Model Size (MB)		
	CNN	DenseNet	DeepNets	CNN	DenseNet	DeepNets	CNN	DenseNet	DeepNets
15	120	150	90	5	7	4	100	120	90
30	130	160	100	6	8	5	110	130	100
45	140	170	110	7	9	6	120	140	110
60	150	180	120	8	10	7	130	150	120
75	160	190	130	9	11	8	140	160	130
90	170	200	140	10	12	9	150	170	140
105	180	210	150	11	13	10	160	180	150
120	190	220	160	12	14	11	170	190	160
135	200	230	170	13	15	12	180	200	170
150	210	240	180	14	16	13	190	210	180
165	220	250	190	15	17	14	200	220	190
180	230	260	200	16	18	15	210	230	200
195	240	270	210	17	19	16	220	240	210
210	250	280	220	18	20	17	230	250	220
225	260	290	230	19	21	18	240	260	230
240	270	300	240	20	22	19	250	270	240
255	280	310	250	21	23	20	260	280	250
270	290	320	260	22	24	21	270	290	260
285	300	330	270	23	25	22	280	300	270
300	310	340	280	24	26	23	290	310	280

Conclusion

In this research work, a proposed DeepNets approaches are used on significant advance in the field of mulberry leaf disease detection, which blends deep learning with attention processes. In this work the testing and evaluation demonstrate that DeepNets outperform traditional CNN and DenseNet architectures which focus on the performance metrics like accuracy, precision, and recall. Using attention processes, DeepNets effectively exhibit key characteristics associated to mulberry leaf diseases, yielding more accurate and reliable classification results. The results of the examination for DeepNets indicate that the agriculture and sericulture industries may use them. DeepNets is a helpful tool for automatic diagnosis and detection of mulberry leaf diseases. Its enhanced performance and competitive processing efficiency allow for early interventions and better disease management strategies.

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