International Journal of Data Science and Artificial Intelligence (IJDSAI)
Volume 3, Issue 1, January – February (2025)

RESEARCH ARTICLE

STRAWBERRY LEAF DISEASE DETECTION USING DEEP LEARNING BASED REGNET

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Abstract – Strawberry leaves are affected by fungal diseases by regarding the combination of features concerning about the absence of pathogens and the ideal atmosphere. Even though the fungal diseases occur often in their life cycle, they can weaken entire plants without causing any major impact. In this research a novel STR-REGNET has been suggested for the detection of strawberry leaf disease. The Adaptive Unsharp Mask Guided Filter (AUMGF), which reduces noise and improves key features including textures and edges, is used to preprocess the leaf pictures. The proposed model begins by an image of strawberry leaves, indicating both healthy and unhealthy leaves. An extremely effective Convolutional Neural Network (CNN) architecture called RegNet is utilized for feature extraction. It is used to modify an unprocessed image of strawberry leaves into a feature set that provides information. To transform into features, it makes advantage of pooling and effective convolutional blocks. Three distinct classifications are identified by the performance metrics of the strawberry leaf disease detection image: normal, powdery mildew, and leafspot. The collected dataset shows that the proposed STR-REGNET model obtains an overall accuracy of 95.85%. The proposed RegNet model's accuracy was greater than that of DenseNet, ResNet, and ResNest by 4.52%, 5.61%, 3.14%, 17.02%, and 8.9%, respectively. The proposed STR-REGNET model is better than CNNs, VGG 16, CNN, and SVM in terms of total ACC, obtaining 2.37%, 6.5%, 0.05%, and 18.17%, respectively.

Keywords – *Strawberry Leaf Disease, Adaptive RegNet, Powdery Mildew, Deep Learning, Adaptive Unsharp Mask Guided Filter, RegNet, Spiking Neural Network, Convolutional Neural Network.*

1. INTRODUCTION

The impacts of an infection on strawberry plants are getting more serious. The two fungal diseases that harm strawberry plants are leafspot and powdery mildew [1]. Plant diseases are the source of today's farming productivity loss, these diseases have an adverse effect on agricultural crop yield. [2]. Fungal infections including leafspot and powdery mildew are a major cause of strawberry crop yield loss. Farmers apply fungicides on a regular basis throughout the seasons to stop these diseases from spreading [3]. The manual approach of identifying the disease of strawberry's symptomatic leaf spots is hard and time-consuming, which increases the likelihood that the ideal moment to implement control measures will be missed [4]. In addition to potentially resulting in significant financial losses, these illnesses significantly lower strawberry production's yield and quality. Plant diseases are difficult to avoid and treat due to their great variety and complex etiology. Traditionally, farmers' visual inspections are used to identify plant diseases early on [5].

This situation is further complicated by the reducing workforce in farms, as it is more difficult to estimate the severity of diseases on a large scale. It is necessary to develop an automated, quick, and specific method for identifying strawberry disease [6]. Farmers don't utilize CNN due to the absence of the data needed to identify diseases using scientific techniques [7]. The use of convolutional analysis in the CNN model plays a vital role in improving disease classification accuracy. Convolution is a procedure in CNN models that extracts features from images and enhances significant characteristics for classification [8]. Many agricultural applications, such as disease diagnosis, plant species identification, and environmental condition monitoring, have successfully used by CNN [9]. The need for of chemical treatments to control the illnesses raises production costs and has the capacity to interfere with sustainable farming methods [10].

When strawberry leaves shows sign of attack gray mold will grow on the damaged area under low temperatures and high humidity, which will cause strawberry fruit to deteriorate. Strawberry plant leaves may get localized patches due to anthrax [11]. The most prevalent method of detecting plant diseases in rural areas is observation, which makes disease detection very difficult. An accurate method for identifying multiple types of strawberry fungal diseases on a single leaf is therefore required [12]. Plants with significant economic worth and bright futures. A key strategy for raising crop quality and yield is to effectively protect plants against disease [13]. In contrast to other crops and periods, strawberries are especially susceptible at this stage to pests and illnesses, even if all crops are at risk. Not protecting strawberry seedlings from foliar diseases and pests can Although they are a very valuable crop, strawberries are vulnerable to illnesses and pests while seedlings [14]. Finding and creating an effective strategy for the adaptive management of strawberry diseases is essential [15]. The following are the research's primary contributions:

- This research proposed a novel STR-REGNET to detect multiple strawberry leaf diseases in early stages. At first the AUMG filter is used to denoised and enhance the images of the infected leaves in order to reduce noise and increase image quality.
- RegNet is used as a robust feature extractor based on the modular structure. It is used to extract texture, color, and shape from the infected leaf images in the listed images.
- The classification of SNN is to classify low and high accuracy of 95.85%. Also performs traditional models like AlexNet, DenseNet and SVM that accurately detects multiple diseases on a single leaf.
- Further, a layer that executes the classification divides the images of affected strawberry leaves into three classes: normal, leafspot, and powdery mildew.

The remainder of the experiment is arranged as follows. The proposed method for detecting strawberry leaf disease using infected images is described in Section 4, the experimental findings and discussion are illustrated in Section 3, that covers a literature review is provided in Section 2, and future work is concluded in Section 5.

2. LITERATURE SURVEY

In order to prevent leaf disease, researchers have recently proposed various methods for detecting strawberry leaf disease. This section provides an overview of several current machine learning (ML) and deep learning (DL) experiments that describe different images of infected strawberry leaves.

In 2024 Wu, J., et al, [16] proposed ResNet9-SE Squeeze-and-Excitation (SE) model for strawberry plant disease detection. The dataset for the proposed algorithm shows that it can achieve excellent diagnosis accuracy with fewer parameters and minimal memory usage. The ResNet9-SE's experimental classification of the final accuracy result is 97%, indicating that it is appropriate for distribution in embedded systems.

In 2024 Chen,W., et al, [17] proposed RT-PCR detection determined 65 of the 159 strawberry leaf samples. The 65 positive samples were isolated, sequenced, and cloned to produce three SMoV isolates. According to sequence similarity analysis, the range of amino acid nucleotide identity and consistency was 94.68% to 99.53%, while the range for amino acids was 98.12% to 99.84%.

In 2024 Nguyen, D.K., et al [18] proposed a U-Net of an effective method based on multitask to distinguish types and estimate the importance of strawberry leaf disease. The model that is most efficient being the one suggested, which has the VGG16 backbone. The classification of a difficult background dataset outperformed the performance of current classification models, achieving values for accuracy, precision, recall, and F1-score of 99.18%, 98.90%, 99.03%, and 98.93%, respectively.

In 2024 Singh,N., et al, [19] proposed ResCBAM-CNN model was configured on the edge device, the test dataset's plant images were utilized to evaluate it. The integration of residual connections improves the transmission of information, leading to more thorough feature representations and enhanced classification skills of the ResCBAM-CNN model. Out of all the suggested models, the ResCBAM-CNN gave the best performance. With precision, recall, accuracy, and F1-score values of 82.0%, 83.0%, 82.5%, and 82.7%, respectively.

In 2024 Prince, R.H., et al, [20] proposed CNN-SVM model by the potential of improving plant disease classification's precision and effectiveness. The CNN-SVM model was chosen over VGG16 and other models due to its greater accuracy metrics. The proposed model is comparable to the VGG16 pre-trained model in terms of accuracy. The proposed model has an average accuracy of 99.09% and an F1-score of 99.98%.

In 2025 Chen,M., et al, [21] proposed YOLOv8-model of improved segmentation technique for identifying lesions and leaves. Segmenting strawberry leaves and lesions in their natural environments is a challenge that is necessary for accurate disease identification. In comparison to the YOLOv8-seg baseline, the results demonstrate that the segmentation accuracy is 92%, the recall is 85.2%, and the mean average is 90.4%. These values are 4%, 2.9%, and 4% higher, respectively. The improved model has grown by 3.9%, 5.8%, and 14.8%.

In 2024 Mi, Z. and Yan, W.Q., [22] suggested YOLOv9 and Swin Transformer models to accurately determine the freshness of strawberries. This model outperforms the 86.1% mAP model that solely uses YOLOv9. Using the metric intersection, our model achieves a mean precision (mAP) of 87.3% after being trained and assessed on a well-chosen dataset. Improved precision and recall, which rose to 85.3% and 84.0%, respectively, further demonstrated our model's ability to accurately and consistently distinguish between the different stages of strawberry ripeness accordingly.

In 2023 Pang,F., et al, [23] proposed MS-YOLOv5 of enhancement technique based on YOLOv5. It entails replacing the traditional convolution with the depth hybrid deformable convolution (Ms-MDconv) in order to change the MS-YOLOv5 feature extraction network. Using the strawberry ripeness dataset, the method was tested; the FPS was 76, the mAP was 0.956, and the model size was 7.44M. 96.51% is the final accuracy of the proposed model.

In 2024 He, Y., et al., [24] suggested KTD-YOLOv8 model that automatically detect strawberry leaf diseases, improving speed and accuracy. The conventional component of the YOLOv8's backbone is replaced with the Kernel Warehouse convolution in order to minimize the computational complexity. Comparing KTD-YOLOv8 to the original YOLOv8, the experimental results indicate that the mAP@0.5 increases from 86.9% to 89.7%.

In 2025 Darlan,D., et al, [25] suggested EfficientNetB7, a new AI integration in agriculture that focuses on the particular difficulty of classifying strawberry plant growth stages for the best possible nutrition management. The research identifies common errors in the literature, such as ineffective technique, a lack of benchmarking, and datasets that are either inaccessible or limited. To address these issues, provide a comprehensive dataset based in a greenhouse that spans seven different stages of strawberry growth and was recorded in a variety of settings. The experiment shows an 83.1% final accuracy.

The project's main objective is to fulfill the need for the identification and appropriate management of a variety of flower diseases. This used to be a difficult task, but now the farmer may easily identify plant illnesses by taking images of their leaves. For disease identification, we mostly used image processing techniques to modify the data in order to increase the CNN model's accuracy. This approach can produce results instantly and provide a suitable solution.

3. PROPOSED METHODOLOGY

The ARN-model workflow for detecting strawberry leaf disease is described in the diagram. An Adaptive Unsharp Mask Guided Filter is used to enhance important features such as edges and textures while reducing noise . The RegNet model receives the improved image and uses its deep learning layer to extract patterns like color and texture.The SNN receives the collected information and correctly classifies the leaf state as Normal, PowderyMildew, or Leaf spot. Even when a single leaf exhibits several symptoms, our methodical technique guarantees efficient disease detection

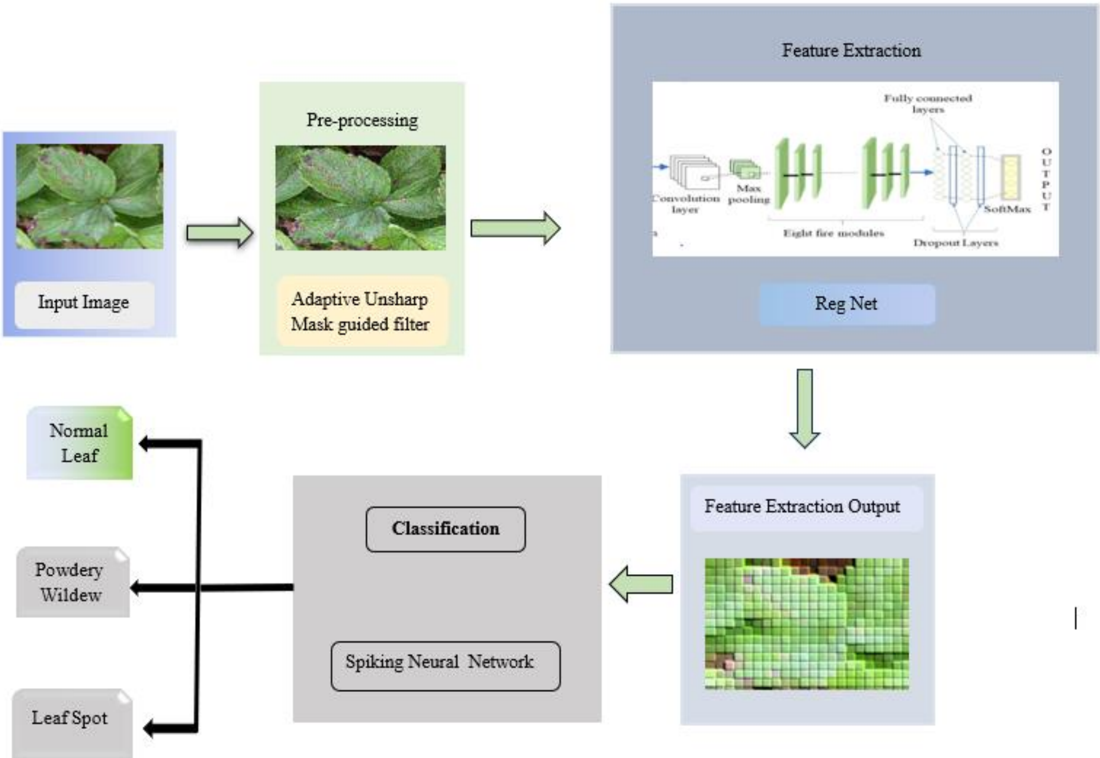

Figure 1. The Proposed Methodology of ARN-Model

3.1 Dataset Description

The detection of plant diseases, the only widely accessible dataset is Plant Village. With an accuracy of 95.85%, the data set curators developed an automated approach for disease identification using RegNet and AlexNet. However, the Plant Village dataset's images were taken in laboratories instead of in real agricultural fields, thus their application is probably going to be limited. On the other hand, in order to produce a widely accessible dataset, we select real-life images of both healthy and diseased plants.

3.2 Adaptive Unsharp Mask Guided Filter for Pre-Processing

The AUMGF is a preprocessing method used in leaf disease detection to enhance visual details, drawing attention to disease spots and uneven textures. The first image used in the process is a leaf, often captured in either natural or artificial lighting. Initially, the image is subjected to a guided filter. Unlike other blurring techniques, this filter maintains important edges, including leaf veins and boundaries, while producing a smoother version of the image with less noise. A method of image processing called an AUMFG combines the edge-preserving qualities of guided filtering with the sharpness-enhancing potential of unsharp masking. Particularly in low-resolution regions, this combination enables selective sharpening, boosting detail while reducing undesirable effects like halo artifacts and noise amplification.

This base image is then subtracted from the original image to determine the detail layer. Spots, fungal lesions, textural variations, and infected patches are examples of high-frequency details that are captured by this layer.

$$I_{sharp} = I + k \cdot (I - G_{\sigma}(I)) \tag{1}$$

Then, an adaptive weight map (α) is calculated to make sure that sharpening is used sparingly. By analyzing the image's local statistical properties, such as texture complexity, gradient magnitude, or local variance, this map is produced. Areas with noticeable edges or texture changes are assigned high α values, whereas smoother parts are assigned lower α values. In order to manage the sharpening intensity pixel-by-pixel, the adaptive α map is multiplied by the detail layer to create the weighted detail layer. After this, the weighted detail is added back to the original image to create final improved image, which produces an output with more distinct and noticeable disease-affected areas.

$$I_s(x, y) = I(x, y) + \alpha(x, y) \cdot (I(x, y) - I_b(x, y)) \quad (2)$$

The original image serves as the basis for enhancement in this case, and the input image is $I\ (x, y)$. To create a smooth version of the original image while maintaining its edges, a guided image is applied. By deducting the smoothed image from the original image, the detailed layer $D\ (x, y)$, is determined.

$$D(x, y) = I(x, y) - I_b(x, y \quad (3)$$

In this way, high frequency elements such as edges, textures, and disease spots are captured. A weight map called $\alpha(x, y)$ serves as the adaptive coefficient, which changes according to local image features and the sharpened output. The final enhanced output image, $I_s(x, y)$, is produced by overlaying the original image with the weighted detailed layer.

$$I_s(x, y) = I(x, y) + \alpha(x, y) \cdot D(x, y) \quad (4)$$

$$I_{final} = Guided\ Filter(I + k(i) \cdot (I - G_\sigma(I)),\ G) \quad (5)$$

An improved image with fine details and more evident disease signs is perfect for additional processing, such as segmentation in a leaf disease detection system.

3.3 RegNet for Future Extraction

RegNet is effectively converts raw leaf images into condensed, high-level representations for the detection of strawberry leaf diseases, serving as a solid basis for feature extraction ,known as the "stem,". RegNet, an effective CNN, was created to automatically produce effective network topologies by modifying key network parameters and applying a set of predictable design rules. The process begins with a main convolutional layer that records low-level characteristics including vein patterns, leaf margins, and early indications of deterioration. According to a quantized linear rule, RegNet is divided into four main stages, each of which increases the number of channels:

$$w_i = quantize(w_o + w_a \cdot i, q) \quad (6)$$

The network can gradually capture increasingly complex and abstract properties, such as textures, lesions, and shape deformations associated with disease, thanks to this architecture. To allow the network to learn several complementing patterns at once, each stage consists of grouped convolutional blocks, also known as bottleneck blocks, which divide feature maps into smaller groups. In strawberry leaves, this feature is especially helpful for identifying fine-grained disease symptoms like vein blight, black patches, or powdery mildew.

$$C(i) = quantize(C_0 + i \cdot \Delta) \quad (7)$$

Batch normalisation and non-linear activation functions such as ReLU or Swish are utilized to further stabilise the learning process and maintain the small visual variations in the leaf texture. As the data moves farther into the network, the semantic richness increases and the spatial resolution decreases.

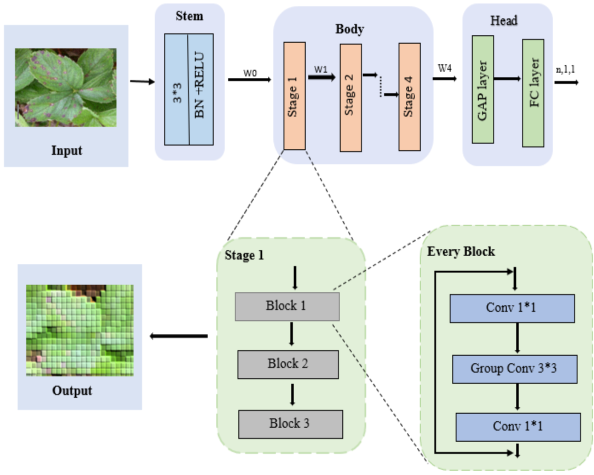

Figure 2. Architecture of RegNet

The most important information extracted from the leaf image is captured in a one-dimensional vector by compressing the spatial features at the end of the feature extraction process using a global average pooling layer. This vector is then sent to a detection head or classifier, which uses the learnt features to assign a disease label. As a result, it is ideally suited for edge-based and real-time applications in smart agriculture.

$$w_i = w_0 + k \cdot i \quad (8)$$

where w_(i) is the width at stage I, w_0 is the width's initial stage, and w_a is the slope that decides whether to widen the width. The width result is used in a predetermined factor q.

$$w_i = round\_to\_multiple(w_0 + k \cdot i, q) \quad (9)$$

The network may grow methodically because to this quantized width scaling, which also makes it compatible with modern GPU/TPU hardware.

$$w_i' = quantize\ (w_i, q) \quad (10)$$

$$W_q(i) = q \cdot \left\lfloor \frac{w(i)}{q} \right\rfloor \quad (11)$$

RegNet uses bottleneck blocks with group convolutions in each step, which divide the feature maps into groups and process them simultaneously. The network can more easily learn a range of local patterns, including lesions, white powdery textures, or necrotic patches, which are commonly observed on damaged strawberry leaves, thanks to this group-oriented architecture. RegNet collects increasingly abstract elements as the leaf image moves through various phases, ranging from simple textures in the early layers to complex disease-specific patterns in the latter layers.

$$N = | \{w_q(i) \mid i = 0,1,\ldots,D-1\} | \quad (12)$$

A feature vector is created from the high-dimensional feature maps using GAP, which captures the spatial properties throughout the image, after the feature extraction stage is finished. The final disease classification, such as healthy, leaf scorch, powdery mildew, or bacterial blight, is then generated by this feature vector and sent to a fully connected layer.

3.4 Spiking Neural Network for Classification

In Spiking Neural Network, the strawberry leaf images are converted into spiked based on the features of colour, shape and texture. SNN finds to understand the specific spike patterns like healthy or diseased leaves. SNNs are thought to be more biologically accurate than artificial neural networks. SNNs are extremely appealing for technical applications, particularly in portable devices, because they are less energy-intensive and more compatible with hardware than ANNs. There are many difficulties in training deep SNNs. Backpropagation is hampered by the transfer function of spiking neurons, which is typically non-differentiable.

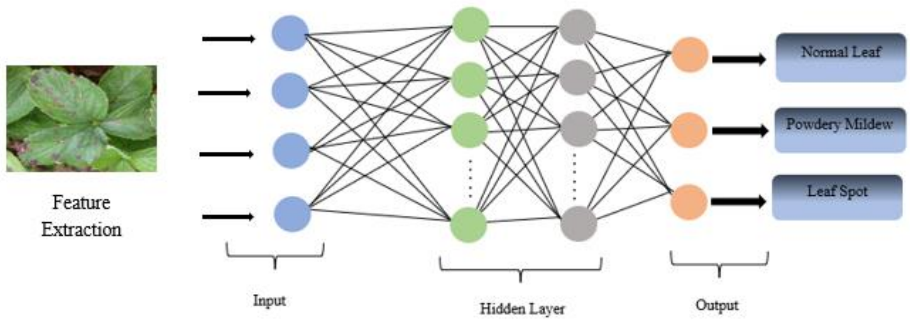

Figure 3. Architecture of SNN

Through this review, we compare contemporary supervised & unsupervised methods for deep SNN training in terms of hardware compatibility, accuracy, and computational cost. According to the new trend, SNNs generally require a lot less operations than ANNs, but even while they still lag behind ANNs in accuracy, the gap is closing and might potentially vanish for some applications.

A spiking neuron modifies its membrane potential (Vm) by incorporating incoming spikes, adjusted according to their strength.

$$Vm\,(t+1) = Vm(t) + \sum(w_i.spike\_input_i(t)) - Vm_{reset} \quad (13)$$

$$Vm\,(t+1) = Vm(t) + \sum(w_i\,.spike\_i\,(t)) - \lambda\,.V\_m(t) \quad (14)$$

Images of both healthy and damaged leaves must be collected in order to use an SNN to identify strawberry leaf disease. Spike encoding is used to convert these images into spike patterns, simulating the human visual system by producing more spikes from brighter pixels. The spike data is processed by spiking neurons that are according to the Leaky Integrate-and-Fire concept. A neuron is said to be active when its potential is surpassed.

$$V_m(t) \leftarrow V_{rest} \quad (15)$$

The network learns to recognize key characteristics like spots, color shifts, and texture changes as the spikes go through it. The network classifies the disease in the final stage by using the spike counts seen in the output layer. For example, a greater spike count in neuron A indicates a healthy leaf, while neurons B or C can indicate particular diseases like Powdery Mildew or Leaf Scorch.

$$V_m(t) = \sum_j w_j.\epsilon(t - t_j) \quad (16)$$

The potential membrane in the Spike Response Model (SRM) is calculated by adding the affects of previous spikes, each of which is modified by a response function that decreases with time and altered based on its synaptic weight. For uses like image or signal categorization, this mechanism helps the neuron remember information about recent activity and identify temporal trends.

$$\hat{y} = arg\ \max_c \left(\frac{1}{T} \sum_{t=1}^{T} S_c\,(t) \right) \quad (17)$$

In the SNN classification layer, every output neuron represents a distinct illness category. The number of spikes from each class neuron is recorded over a simulation period T. The projected class$\hat{y}$ has the highest average spike rate, based on the calculation that follows. where Sc (t) is class c's output at time t. Finally, the class with the highest number of spikes is defined.

4. RESULT AND DISCUSSION

This section describes the experimental setup that was utilized for the analysis. It was carried out using a PC with an Intel i3 2.10 GHz processor, 8GB of RAM, and Windows 10 OS. The main objective was to develop a deep learning model that could effectively detect Powdery Mildew and Strawberry Leafspot. Figure 4 displays experimental findings using the suggested methodology.

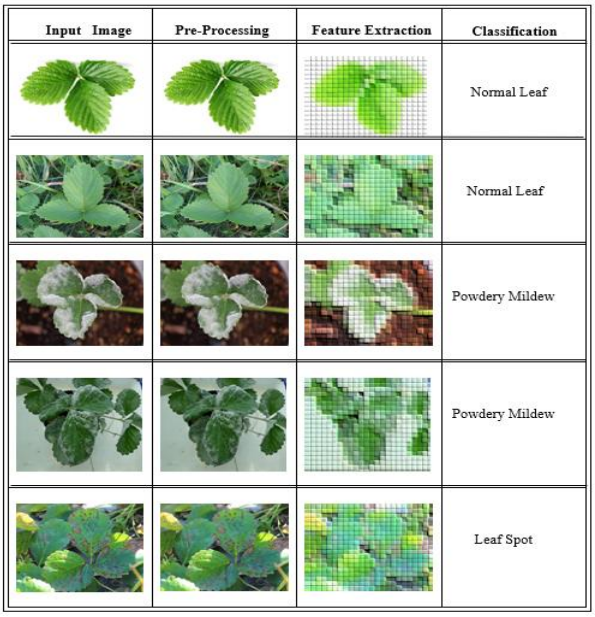

Figure 4. Experimental Results of the Proposed STR-REGNET Model

The diagram illustrates the four primary steps in strawberry leaf disease detection: input image, pre-processing, feature extraction, and classification. Pre-processing is the first stage in enhancing raw leaf pictures, which comprise both healthy and diseased samples. Then, by removing characteristics like color and texture, patterns can be discovered. Based on these attributes, the method classifies each leaf as Normal, Powdery Mildew, or Leaf Spot. This visual process confirms that the model can correctly distinguish between healthy and sick leaves.

4.1 Performance Analysis

Common classification criteria used to evaluate the performance analysis detection system include the model's overall efficacy, recall, specificity, accuracy, and precision. These metrics are defined using the classification findings' counts of true positives, true negatives, false positives, and false negatives.

$$\mathrm{SPE} = \frac{N_{true}}{N_{true}+P_{false}} \quad (18)$$

$$\mathrm{PRE} = \frac{P_{true}}{P_{true}+P_{false}} \quad (19)$$

$$\mathrm{REC} = \frac{P_{true}}{P_{true}+N_{false}} \quad (20)$$

$$\mathrm{ACC} = \frac{P_{true}+N_{true}}{\text{Total no.of samples}} \quad (21)$$

$$\mathrm{F1} = 2\left(\frac{PRE*REC}{PRE+REC}\right) \quad (22)$$

Where P_true and P_false stand for false-positives and false-negatives, respectively, and N_true and N_false for true-positives and true-negatives.

Table 1. Performance Metrics of Strawberry Leaf Detection by Class

Classes	ACC	SPE	PRE	REC	F1
Normal	98.57	92.50	91.35	97.4	90.65
Powdery Mildew	95.20	89.60	92.22	94.42	89.78
Leaf Spot	93.78	99.42	90.56	98.84	96.45

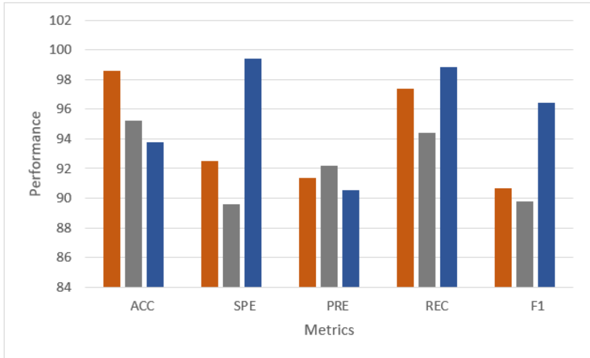

Figure 5. Graphical Evaluation of the Proposed STR-REGNET Model

Table 1 displays the results of the suggested ARN-model for the gathered datasets, i.e., for categorizing illnesses of strawberry leaves. The effectiveness of the suggested ARN-model is shown in Figure 6 for the three classes of Leaf Spot, Powdery Mildew, and Healthy Leaf. The proposed STR-REGNET model has the following total scores: 95.85%, 93.84%, 91.37%, 96.88% and 92.29% for ACC, SPE, PRE, REC, and F1-score, respectively.

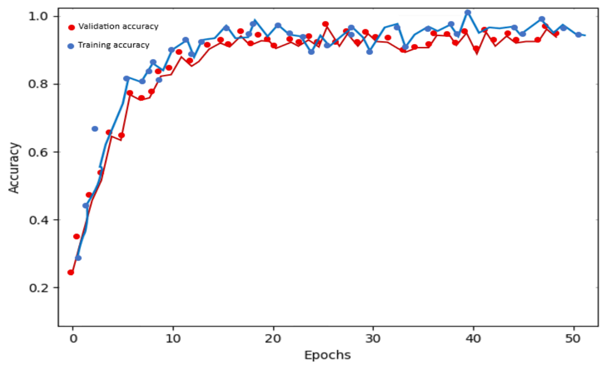

Figure 6. ACC Curve of the Proposed STR-REGNET Model

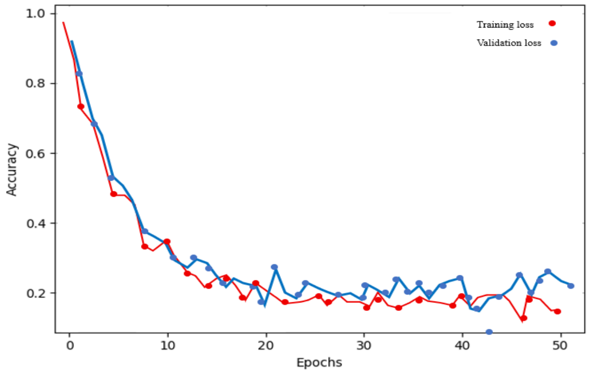

Figure 7. Loss Curve of the Proposed STR-REGNET Model

Figure 6 displays the ACC and loss graph for the suggested STR-REGNET model. The figure shows the accuracy curve with accuracy and epochs on opposing axes. The more epochs there are, the higher the model's accuracy. Figure 7 shows the epoch vs. loss curve, which indicates that the framework's loss lowers as the number of epochs grows. 95.85% is the overall accuracy of the proposed ARN-model.

4.2 Comparative Analysis

This evaluation compares, the suggested STR-REGNET model was contrasted with a number of current methods using various efficiency criteria. The accuracy of 95.85% is attained by the suggested STR-REGNET model. The accuracy rate demonstrates how much more effective the suggested model is than current methods. This assessment contrasted the suggested STR-REGNET model with conventional networks like AlexNet, DesnseNet, ResNet, and RegNet.

Table 2. Comparison of different conventional networks

Networks	ACC	SPE	PRE	REC	F1
AlexNet	91.33	88.23	88.23	79.86	83.39
DenseNet	93.81	89.19	81.98	88.62	85.21
ResNet	95.12	91.40	84.45	91.22	87.62
ResNest	92.17	91.90	89.84	92.48	90.37
RegNet	95.85	93.84	91.37	96.88	92.29

In Table 2, the highest classification accuracy of many traditional DL networks is compared. Across all criteria, AlexNet has the lowest scores, indicating its comparatively poorer effectiveness, whereas DesnseNet and ResNet perform moderately. RegNet comes in second with excellent results across the board.

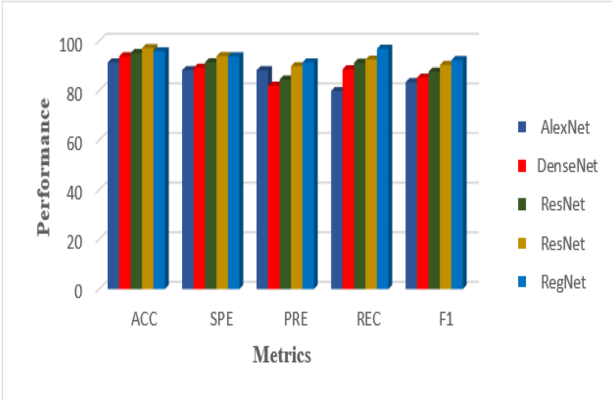

Figure 8. Graphical Comparison of Traditional Detection Network

The suggested RegNet performs better, as seen by its higher accuracy of 95.85% and F1 score of 92.29%. The graphical analysis of the conventional feature extraction networks is shown in Figure 8. In comparison to AlexNet, DenseNet, ResNet, and ResNest, the accuracy of the suggested RegNet model increased by 4.52%, 5.61%, 3.14%, 17.02%, and 8.9%, respectively. Based on the previously addressed network characteristics, the RegNet network outperformed the other conventional networks.

Table 3. Comparison of Proposed ARN- model vs Existing Model

Authors	Methods	Accuracy
Tariqul Islam, M. and Tusher, A.N., [7]	CNNs	93.63%
Sari, E.L.I.P., et al., [8]	VGG 16	90%
Kondaparthi, A.K., et al., [9]	CNN	95.8%
Zhang, B, et al., [11]	SVM	81.11%
Proposed	STR-REGNET-model	95.85%

The comparison between the suggested model based on the collected dataset and several current approaches is shown in Table 3. The total ACC is improved by the suggested STR-REGNET model by 2.37%, 6.5%, 0.05%, and 18.17%, respectively, over CNNs, VGG 16, CNN, and SVM. From the above comparison the proposed AUMG model yields higher accuracy than the existing models. From this overall comparison analysis, the proposed STR-REGNET model is the best based on accuracy and statistical significance in the Strawberry leaf disease detection.

5. CONCLUSION

A specific STR-REGNET model for multiclass classification of strawberry leaf disease based on early-stage pictures of affected leaves was given in this research. The AUMGF filter is mostly used to pre-process the input leaf photos in order to lower noise and enhance image quality. Because of its scalable nature, a RegNet is employed as a reliable feature extractor. A RegNet model is utilized to extract texture, structural features, color, and shape from the infected leaf images in order to perform feature extraction on the categorized images. The classification of SNN is to classify low and high accuracy of 95.85%. Also performs traditional models like AlexNet, DenseNet and SVM that accurately detects multiple diseases on a single leaf. Further, the classification is performed by a layer which classifies the infected strawberry leaf images into three different classes: normal, powdery mildew and leafspot. The proposed RegNet model attains the accuracy was increased by 4.52%, 5.61%, 3.14%, 17.02% and 8.9% over AlexNet, DenseNet, ResNet and ResNest respectively. The proposed STR-REGNET model outperforms CNNs, VGG 16, CNN, and SVM in terms of total ACC, obtaining 2.37%, 6.5%, 0.05%, and 18.17%, respectively. Future research might create lightweight variants of the model to maintain accuracy while lowering processing requirements. Other optimization models can also be assessed in order to enhance performance and hyperparameter modification.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

FUNDING STATEMENT

Not applicable.

ACKNOWLEDGEMENTS

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

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Arrived: 29.01.2025
Accepted: 28.02.2025