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TEADIS: Deep learning based tea leaf disease classification and segmentation via field observation data

[TEADIS: Clasificación y segmentación de enfermedades de hojas de té basada en aprendizaje profundo mediante datos de observación en campo]

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Abstract: Globally, tea leaf diseases significantly impact economic growth, production, and crop quality. This research proposes a novel Deep learning-based TEADIS framework to identify the tea leaf diseases. Initially, visual and digital data are gathered from the Internet of Things (IoT) devices and stored through Sigfox in the cloud environment. The visual data are pre-processed utilizing a scalable range-based adaptive bilateral filter (SCRAB) to remove noise from tea leaf images. The GoogLeNet with GeLu activation function is employed to classify the tea leaves into normal and abnormal leaves. The digital data from the environmental field are used to detect the occurrence of tea diseases for segmentation. Attention V-Net is used to improve segmentation accuracy with attention mechanisms to focus on relevant regions for enhancing the precision of identifying the affected areas. The proposed TEADIS model attained an accuracy of 97.77% based on the gathered the data from the year 2021-2023.

Keywords: Sigfox; TEADIS; GoogLeNet; GeLU activation function; Attention V-net..

Resumen: A nivel mundial, las enfermedades de las hojas de té impactan significativamente el crecimiento económico, la producción y la calidad del cultivo. Esta investigación propone un novedoso marco TEADIS basado en aprendizaje profundo para identificar las enfermedades de las hojas de té. Inicialmente, se recopilan datos visuales y digitales de dispositivos del Internet de las Cosas (IoT) y se almacenan a través de Sigfox en un entorno en la nube. Los datos visuales se preprocesan utilizando un filtro bilateral adaptativo basado en rango escalable (SCRAB) para eliminar el ruido de las imágenes de hojas de té. Se emplea GoogLeNet con función de activación GeLU para clasificar las hojas de té en normales y anormales. Los datos digitales del campo ambiental se utilizan para detectar la ocurrencia de enfermedades del té para su segmentación. Se usa Attention V-Net para mejorar la precisión de la segmentación con mecanismos de atención que se enfocan en regiones relevantes para mejorar la precisión en la identificación de las áreas afectadas. El modelo TEADIS propuesto alcanzó una precisión del 97.77% basado en los datos recopilados entre los años 2021 y 2023.

Palabras clave: Sigfox; TEADIS; GoogLeNet; función de activación GeLU; Attention V-net

INTRODUCTION

A functional beverage with a delicious taste, and organic benefits, tea is a popular choice around the world (Latha *et al*., 2021). Globally, tea is the most frequently drunk beverage and is cultivated as a cash crop in hot, humid climates (Chen *et al*., 2019). To make tea, tea plants are picked, and their fresh leaves are dried. According to a recent survey, three billion cups of tea are consumed daily by people globally (Klepacka *et al*., 2021). The tea can offer health care, hygiene, environmental protection, and safety. Every year leaf blight and other diseases can cause a 20% reduction in the quantity of tea harvested (Bao *et al*., 2022). To minimize losses in tea production, enhance tea quality, and boost tea farmers' revenue, it is crucial to research the precise detection and prediction of tea illnesses (Singh *et al*., 2023).

The production of tea leaves is seriously compromised by several illnesses that interfere with healthy leaf development (Mukhopadhyay *et al*., 2021). It is possible to resolve the issue if the right remedies are applied early on to the contaminated leaf to stop the spread. Many tea gardens now employ manual detection to identify tea illnesses, which waste time, money, and labor (Yuan *et al*., 2019). It is therefore necessary to develop an efficient tea disease to assist tea farmers in identifying diseases and preventing them. A technology-based method for disease detection is crucial to assist farmers in detecting the disease at its earliest stage (Hu *et al*., 2021). Artificial intelligence has played a significant role in the autonomous identification of plant ailments (Yashodha & Shalini, 2021). Machine learning (ML) and Image processing frameworks are utilized to automatically predict and classify crop illnesses (Hossain *et al*., 2018; Srivastava & Venkatesan, 2020). To automatically extract crop disease features and more precisely detect plant illness, deep learning has recently been applied to crop disease detection (Chakraborty *et al*., 2022; Xue *et al*., 2023).

The significant flaw of these techniques is to identify the disease based on visible symptoms (Raja Kumar *et al*., 2023). Typically, a disease at this stage is incurable and causes considerable damage to crops. Plants should be prevented from being damaged by diseases by using solutions that can predict their appearance (Sun *et al*., 2019). Furthermore, disease attacks are strongly correlated with environmental conditions (Maris Murugan & Jeyam, 2023; Devaki *et al*., 2024). It is therefore possible to detect plant diseases based on environmental conditions. In this work, a novel DL-based TEADIS has been introduced to identify tea leaf diseases based on IoT.

The key contributions of the TEADIS framework are as follows:

- The key contribution of this research is to propose a novel Deep learning-based TEADIS framework to identify tea leaf diseases based on the IoT.
- The gathered visual and digital data from the IoT devices are stored through Sigfox in the cloud environment. The visual data are pre-processed using a SCRAB filter to remove noisy artifacts and enhance the edges of tea leaf images.
- The novel deep learning-based GoogLeNet with GeLu activation function is employed to classify the tea leaves into normal and abnormal leaves.
- The digital data from the environmental field are used to detect the occurrence of tea diseases for further segmentation. Finally, the proposed method utilizes Attention V-net to segment the affected region of the tea leaf images based on the field observation
- The efficiency of the TEADIS framework has been evaluated using precision, F1 score, sensitivity, accuracy, specificity, Dice score, and Jaccard Index

The remaining portion of this research is organized as follows, the Literature survey is summarized in Section 2 and Section 3 explains the TEADIS technique for identifying tea leaf disease. Section 4 represents the experimental outcomes and discussion. The conclusion and future work is included in Section 5

LITERATURE SURVEY

Serval DL and ML techniques have been introduced by the researchers to detect and segment leaf diseases. A brief description of some recent methods for tea disease detection is presented in this section.

Bhuyan *et al*. (2024), devised a tea leaf disease prediction model using Res4net-CBAM, a deep Convolutional Neural Network. This framework leverages a Res4net with residual blocks and a network-interactive CBAM to extract complex features related to diseases. The suggested designed to diminish the complexity and enhance disease detection accuracy. Yet this model attains limited scalability and difficulty in interpretability.

Bhagat & Kumar (2024), suggested ML and DL techniques for tea leaf disease detection. The color feature is extracted using VGG-16 and classification is done via XGB, KNN, Random Forest, and kernelized SVM. The suggested model aims to reduce overfitting and attains 96.67% of accuracy. However, this model cannot handle high-dimensional images.

Heng *et al*. (2024), presented a tea leaf diseases prediction using AI. Initially, the tea images are preprocessed to eliminate noise, and a hybrid pooling-based CNN is subsequently employed for feature extraction. Once feature extraction is completed, a weighted Random Forest (WRF) model, optimized by Cuckoo Search Optimization (CSO), is utilized for tea leaf disease prediction. The suggested model attains an accuracy of 92.47%. Yet this model suffers from high computational complexity.

Jayapal & Poruran (2023), created an image retrieval technique for identifying the tea leaf images as healthy or unhealthy. Hashing with integrated autoencoders was developed to retrieve the tea Leaf images. The autoencoders utilized the skip connections to provide prominent features in the prior tensor with more weight. It is superior to cutting-edge techniques because its features are integrated with an autoencoder to produce better results. However, the suggested model is sensitive to noise and has difficulties in handling large-scale datasets.

Pandian *et al*. (2023), devised a DCNN for tea leaf diagnosis. The DCNN technique utilizes two convolutional layers, three bottleneck blocks, three dense layers, and several image manipulation methods to produce enhanced tea leaf images. The suggested DCNN yields an accuracy of 98.9% for tea grey blight disease prediction. Yet this model is prone to overfitting.

Datta & Gupta (2023), presented a tea leaf disease prediction based on a DNN. An image classification model based on two-dimensional CNNs and RGB images is developed for Tea Leaf disease. The suggested approach can automatically identify healthy and sick leaves and categorize tea leaf illnesses into five types. This model attains 96.56% of accuracy. Yet, this model holds huge computational costs.

Lin *et al*. (2023), suggested a TSBA-YOLO model for tea disease detection. To validate the test, the dataset is collected from Maoshan Tea Factory in China. Global data on tea illnesses were gathered using the self-attention mechanism. BiFPN feature fusion and Adaptive Spatial Feature Fusion (ASFF) were utilized to enhance the multiscale fusion feature. Small-target tea diseases were identified using the Shuffle Attention mechanism. Finally, the accuracy was increased by using SIoU. However, the suggested model attains difficulty in generalizing to different environmental conditions

Liu *et al*. (2022), devised a blister blight disease detection for tea plants using ML. IoT is used to immediately collect humidity, rainfall, and temperature from the agriculture field. The relationship between environmental factors and disease rates is determined by a regression line model. The suggested technique attains 91% accuracy. However, the suggested model reduced effectiveness in varying climatic conditions.

Nagasubramanian *et al*. (2021), presented an IoT and Ensemble classification-based plant disease monitoring. IoT was used to track and record hyperspectral leaf image acquisition. Images were stored in the cloud and various types of leaf diseases were detected by using CNN and ENSVM. This CNN and ENSVM attained 75% and 80.15% of accuracy. Yet this model utilized a limited dataset.

Bhowmik *et al*. (2020), devised a CNN technique for Rust and Black Rot of tea leaf diseases prediction. The training step begins with obtaining a clear tea leaf image. Next, preprocessing and image labeling are completed, and CNN is used for training. In the subsequent phase, CNN is utilized for the preprocessing and classification for obtaining new test images. Additionally, the model may struggle to generalize to new diseases. Differences between the TEADIS Model and existing frameworks.

The significant research findings and the differences between the current techniques and the TEADIS framework are detailed below:

- The proposed TEADIS framework integrates visual data from IoT devices with environmental data (e.g., humidity, temperature, rainfall) to improve the prediction accuracy. Unlike models like VGG-16 or Res4net, which focus solely on image features, TEADIS leverages both visual and digital data to provide a more holistic view of disease detection.
- TEADIS employs a deep learning-based GoogLeNet with a GeLU activation function for disease classification. This architecture was chosen due to its computational

efficiency and reduced complexity, making it more appropriate for real-time applications.

- Many of the existing techniques, focused solely on disease prediction and categorization, do not consider the segmentation of the disease area during detection. The Attention V-Net used in TEADIS enhances segmentation accuracy by utilizing attention to focus on the utmost relevant regions of the tea leaf images. This is particularly useful for accurately identifying affected areas of the leaf.

From the literature survey, various ML and DL algorithms were utilized for tea leaf disease prediction and segmentation using computer vision techniques from the visible features of tea disease symptoms. An effective solution must be needed to predict and segment diseases to take proactive measures. However, the existing works do not focus on the segmentation accuracy for early detection of tea leaf ailments, that effectively diagnose ailments in tea leaves. To tackle these challenges, a novel TEADIS framework has been proposed to identify tea leaf diseases based on the IoT and DL algorithms.

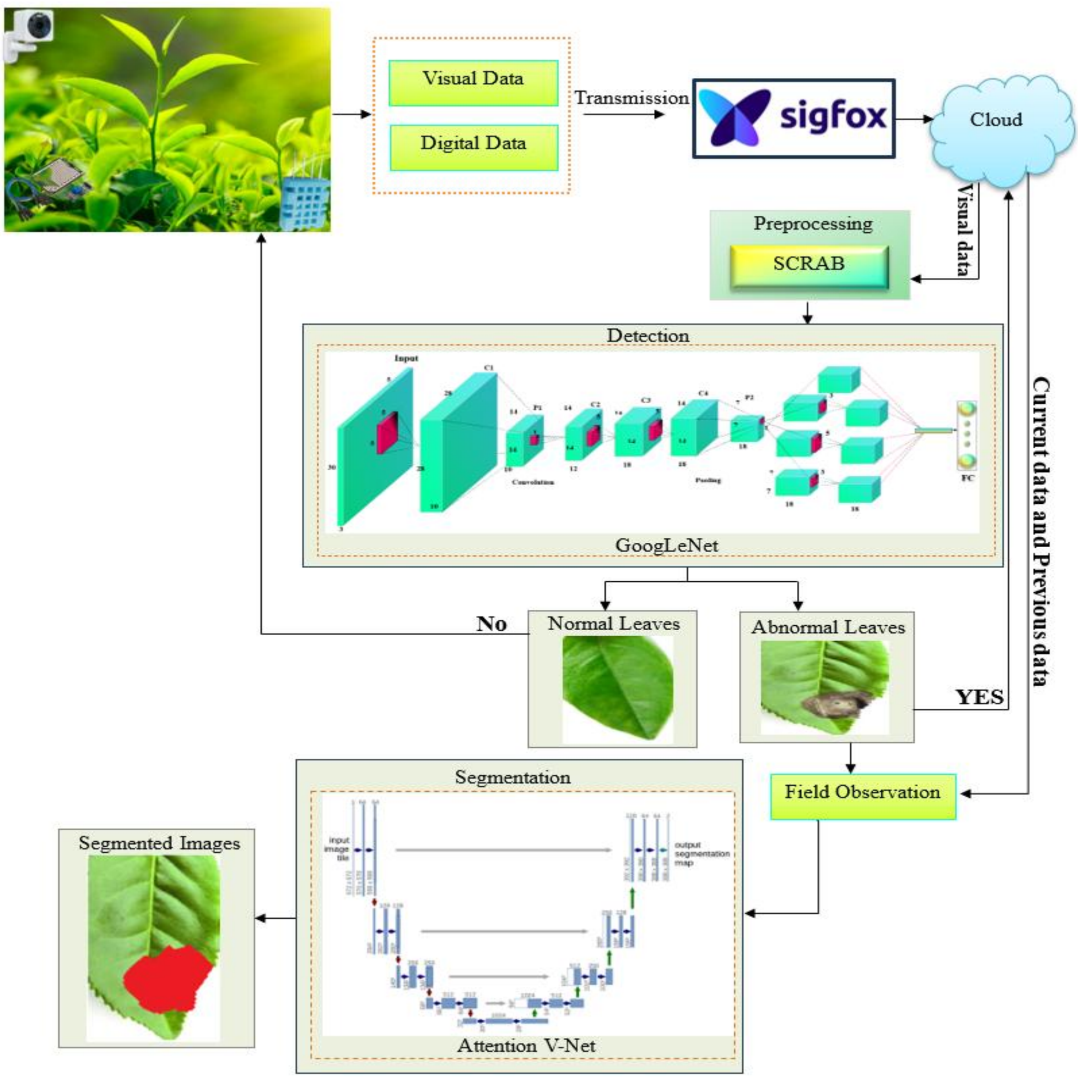


Figure No. 1
The proposed TEADIS framework

PROPOSED TEADIS METHODOLOGY

In this work, a novel DL-based TEADIS model has been proposed to identify tea leaf diseases based on the IoT. Initially, visual and digital data are gathered from the IoT devices and stored through Sigfox in the cloud environment. The visual data are pre-processed using a SCRAB filter to remove the noisy artifacts and enhance the edges of tea leaf images. The novel deep learning-based GoogLeNet with GeLu activation function is employed to classify the tea leaves into normal and abnormal leaves. The digital data from the environmental field are used to detect the occurrence of tea diseases for further segmentation. Finally, the proposed model utilizes Attention V-net to segment the affected region of the tea leaf images based on field observation.

Data collection

The images are gathered from a tea plantation in Ooty, "Homewoodtea," using IoT-based hardware from 2021 to 2023. This included both visual and environmental data. The environmental data was gathered using an Arduino platform with DHT-11 sensors for measuring humidity and temperature, and a rain sensor for rainfall measurement, capturing real-time, accurate readings from the field. For visual data, surveillance cameras were used to collect 1332 images of tea leaves, each originally sized at 512x512 pixels. These images were later resized to 224x224 pixels for input into the GoogLeNet model, optimizing performance while maintaining necessary visual features. The TEADIS framework analyzes both visual and environmental data in the cloud, providing a comprehensive approach to tea leaf disease detection. Despite challenges like inconsistent lighting and sensor calibration, the collected data enhances the generalization and robustness ability.

Humidity

Humidity exhibits the moisture in the air. During the years 2021-2023, the average humidity was calculated by using Equation (1).

$$Hum_{avg} = \frac{\sum_{x=1}^{y} hum_{max}}{y} \tag{1}$$

"(hum_{avg})" represent the monthly humidity, and "(hum_{max})" denotes the maximum daily humidity.

Temperature

Temperature exhibits a strong correlation with disease growth. The monthly Temperature ($Temp_{avg}$) is attained from the daily maximum temperature $Temp_{max}$. The average temperature is computed using eqn (2).

$$Temp_{avg} = \frac{\sum_{x=1}^{y} Temp_{max}}{y} \tag{2}$$

Herein 'y' represents the number of days. The temperature in the chosen location is observed from February to June from the year 2021 to 2023.

Rainfall

Rainfall measures the quantity of rain that occurred on a particular day in a designated month. The maximum rainfall is calculated by using eqn (3)

$$Rain_{max} = max_{rain(avg)} \tag{3}$$

Herein "$Rain_{max}$" denotes the maximum of monthly rainfall, "$rain_{avg}$" is the average of daily rainfall.

SigFox communication

SigFox is a low-power/long-range wireless technology family that is commonly used in the construction of IoT networks where sensors transmit small amounts of information over long distances. SigFox employs a modulation technique known as D-BPSK (Differential Binary Phase-Shift Keying), which operates within a specified bandwidth for data transmission. In contrast to traditional network topologies, this transmission system involves the asynchronous exchange of messages between devices and base stations. The Packet Forwarders send messages from devices to servers through the SigFox gateway. SigFox gateways collect, store, and analyze data in the cloud.

Image preprocessing

Pre-processing is a process utilized to enhance the precise features and eliminate undesired noise from an input image. Herein, the visual data are pre-processed using a scalable range-based adaptive bilateral filter (SCRAB) to remove the noise and enhance the edges of tea leaf images. SCRAB is a non-linear, smoothing, edge-preserving, and noise-reducing filter. The Gaussian distribution function is used to evaluate the weighted intensity means and pixel values of adjacent pixels. Euclidean distances and Radiometric differences are then used to calculate range weight. Noise is significantly reduced by applying this parameter, but image pixels are preserved along their edges.

Bilateral filtering BF(a) for an image is computed using Eq (4):

$$\mathrm{BF(a)} = q_k^{-1}(\mathrm{r}) \int_{\Omega} v(u)x(u,p)y\left(v(u), v(p)\right)da \tag{4}$$

After normalization:

$$\mathrm{q(r)} = \int_{\Omega} x(u,p)y\left(v(u), v(p)\right)da \tag{5}$$

Bilateral filters have some limitations when it comes to capturing edge variations in noisy images. SCRAB is used to fix these issues, and it is computed as follows:

$$R_s(\mathrm{u, p, w}) = w \exp\left(-\frac{1}{2}\left(\frac{\|v(u)-v(p)-w(p)\|}{\sigma_s}\right)\right) + q \tag{6}$$

$$\mathrm{y(x)} = \begin{cases} |R(i) - Mean\,(\Omega_{j})| & |i-j| \leq b \\ o & otherwiswe \end{cases} \tag{7}$$

Where Ω_j denotes the $(2n+1)*(2n+1)$ pixel set of windows where n=2. w and q, Ω_j are the positive parameters which represent the average value; b denotes the stable variable and $w(p)$ represent the range-based function. Sample plant images for after and before preprocessing are illustrated in Figure No. 2.

Figure No. 2
Before and after preprocessed images

GoogLeNet

The preprocessed images are fed into deep learning-based GoogLeNet with GeLu activation function to classify the tea leaves into normal and abnormal leaves. Google Net, also referred to as Inception, is a well-known deep convolutional neural network architecture with 22 deep layers and Inception modules for processing capacity intended for image categorization. The proposed model aims to decrease the training parameters by fine-tuning the number and size of the convolutional kernel, as well as GoogLeNet's core structure. The training application is fully executed with the selected hyperparameters. GoogleLeNet requires tuning its hyperparameters, such as learning rate, neurons, number of epochs, batch size, and activation function, as shown in Table No. 1. The learning rate of the GoogLeNet is 0.001. The proposed model also changed the activation function relu into GeLU. The GoogLeNet architecture is demonstrated in Figure No. 3.

Table No. 1
Hyperparameter of GoogLeNet

Parameters	Values
Number of epochs	50
Number of neurons	512
Activation Function	Gelu
Batch sizes	64
Learning rate	0.001
Dropout	0.4

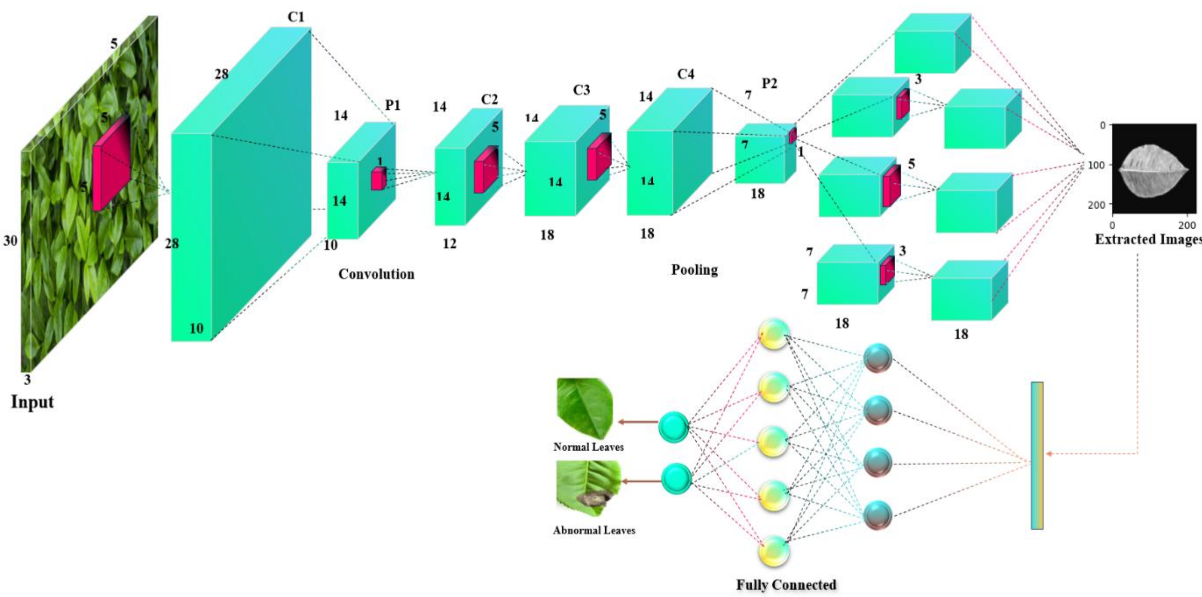


Figure No. 3
GoogLeNet Architecture

Dense-inception

A dense-inception is a structure composed of a densely linked layer and two convolutional layers. The proposed framework reduces the depth of the fully dense connections, ensuring completeness of the feature information, to reduce parameters. Lower layers detect basic patterns such as colors and edges, while in-depth layers identify more complex structures like leaf veins or signs of disease. The network's capacity to detect multi-scale features is essential for identifying subtle distinctions between normal and abnormal leaves. The network utilizes two additional convolutional layers to improve its ability to extract features. The sizes of the two convolutional layers are 1×1 and 3×3. DenseBlock consists of multiple dense layer layers, each of which has two convolution layers. Each convolution kernel assigned to these two layers has a size of 1×1. A batch normalization layer has been placed in between the convolution layer and the activation function to avoid repositioning. This solves gradient disappearance and improves training.

Activation function

A tuned activation function improves the model's training accuracy by improving its accuracy. Models that choose the activation function will have a gradient at infinity that is greater than 0 because the activation function will converge and fade more quickly. ReLU functions are affected by gradient disappearance on the negative half-axis. To overcome these issues GeLu activation function is utilized. The Gaussian Error Linear Unit (GELU) approximates the cumulative distribution function of a traditional Gaussian distribution function, resulting in a smooth, differentiable approximation of the rectifier function.

The mathematical expression for GELU is given by:

$$GELU\ (A) = \ 0.5a(1 + \tanh\ (\sqrt{\frac{2}{\pi}}\ (a + 0.044715\ a^3) \qquad (8)$$

Herein, tanh represents the hyperbolic tangent function. In GELU, nonlinearity is introduced into the network, which allows the technique to learn complex patterns from the data. GELU also behaves like the ReLU activation function in the positive region, where it allows the flow of gradients during the backward pass, similar to ReLU.

In the final stage of the GoogleLeNet network, the feature maps are flattened and fed through fully connected layers for classification. The output from these layers is then fed into a softmax classifier, which assigns probabilities to each class (normal or abnormal). These probabilities are used by the network to determine whether a tea leaf is healthy or abnormal.

Segmentation

In this section, the proposed method utilizes Attention V-net to segment the affected region of the tea leaf images based on field observation. The digital data from the environmental field are also used to detect the occurrence of tea diseases for further segmentation. The architecture primarily consists of an encoder-decoder structure with attention gates to improve segmentation accuracy. Feature extraction is performed by the encoder part, and resolution is restored by the decoder part. V-Net features are extracted using horizontal connections from the encoder to the decoder. These features capture various levels of detail, from basic textures to complex structures in the tea leaf images. A 3D attention gate can be worked as a connection component so that significant structural associations can be produced based on regional weight information paired with feature maps. Figure No. 4 depicts the architecture of attention v-net. This network is composed of four encoder blocks and four decoder blocks connected symmetrically by skip connections between the encoder and decoder. The convolutional network is generally split up into stages in which each stage consists of one to three convolutional layers. Transposed convolution is also used in place of pooling in the upper and lower sampling sections. Furthermore, a structure is provided for the inclusion of residual connections at each level. SoftMax is used to transform the final convolution layer into a probabilistic foreground and background region segmentation.

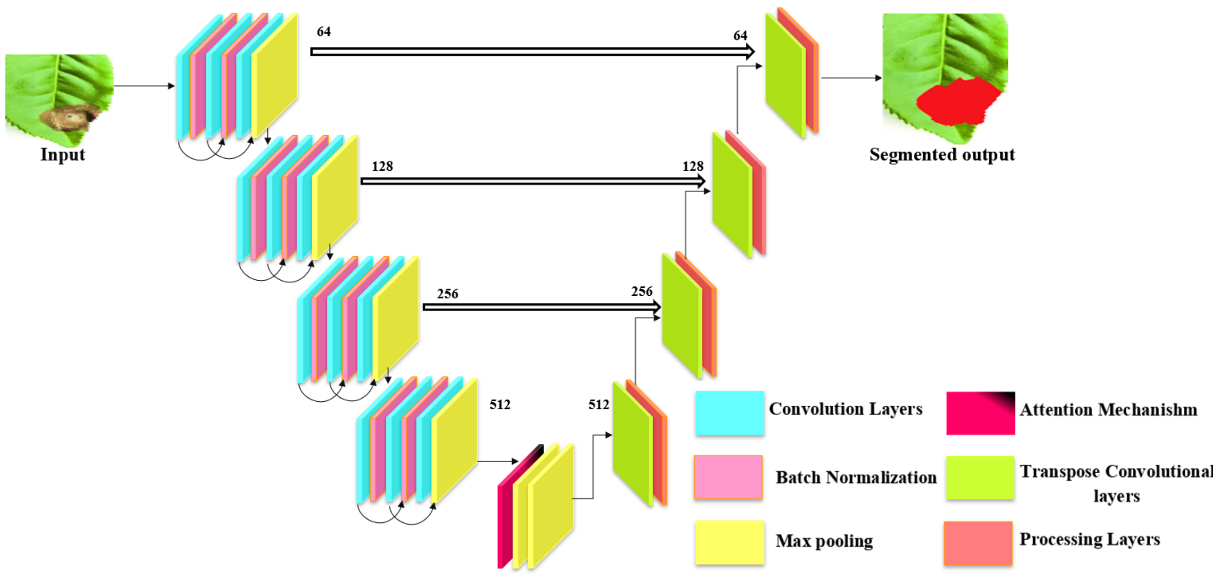


Figure No. 4
Attention V-net architecture

During the image segmentation task, all hidden states play a significant role, but they are not equally significant. Convolution and pooling operations deepen the network through the V-Net. Ultimately, there will be more semantic information in the divided pixels in high-dimensional space. The contextual information from neighboring layers must be combined by a module, and the network must be guided by this information to identify the feature map's regions of interest. Therefore, self-attention is required to vigorously modify the significance of hidden values. In Squeeze Excitation's attention technique, the channels are multiplied by the coefficient of weight. The proposed technique involves applying a distinct adjustment factor to every value within each channel of the feature map. Moreover, the feature maps and spatial weight information may be combined via the developed attention gate to improve semantic information and lower noise.

Attention Gates

A 3D attention gate is integrated into the standard V-Net network for data processing. Each level of skip-connection is preceded by a 3D attention gate, which allows the network to prioritize skip-connection characteristics. It computes attention weights that are used to selectively enhance important features while suppressing less relevant ones. Two inputs are received by a 3D attention gate: one is the feature map F sent using the skip connection from the extended pathway and the second is the feature map P sent by the preceding neural layer. The 1×1×1 convolution receives both F and M, converting them into the same number of channels without altering their dimension. ReLU is used to maintain the number of channels stable and aggregate them based on channel direction after the upsampling process. Next, the output is passed through a sigmoid and one more 1×1×1 convolution. Finally, an attention weight score is obtained by multiplying $\alpha i \in [0, 1]$, which identifies the relevant features of an image. An attention gate produces its output by element-wise multiplying input feature maps and attention coefficients $\hat{F}_{i,m}^{j} = \hat{F}_{i,m}^{j} \cdot \alpha_i^j$. The default setting assigns a single attention value to each pixel vector. $F_{i,m}^{j} = s^{x_j}$ where x_j coordinates to the number of feature maps in layer j. Input feature maps of this layer can be updated with weight information to eliminate irrelevant information. The 3D attention gate output combines contextual information with the next encoder via concatenation, where $A = A_F + A_p$, $B = B_F = B_P$, $C = C_F = C_p$, $R = R_F = R_P$. This could lead to improved segmentation performance with the 3D attention-gate module. The attention weight coefficient is obtained using additive attention as illustrated in the equation:

$$g_{At}^{j} = \varphi^{n}\left(\alpha_1\left(C_F^n F_i^j + C_p^n p_i + d_p\right)\right) + b_{\varphi} \quad (9)$$

$$\beta_i^j = \alpha_1(g_{At}^j(F_i^j, T_i \Theta_{At}) \quad (10)$$

The 3D attention gate is categorized by a set of parameters Θ_{At}containing linear transformation. The linear transformations for the input tensors are computed through a channel-wise convolution. Moreover, g_{At}^{j} represent the transformation operation of two inputs F and P, using the Θ_{At} parameter. The final output of the Attention V-Net, enhanced by 3D Attention Gates, is a 3D segmentation map that emphasizes the regions impacted by the volumetric data. Tea leaves can be accurately identified and delineated as diseased through enhanced features and focused attention.

RESULT AND DISCUSSION

The experimental outcomes of the TEADIS framework were executed using Python, version – 3.11.4 executed on a PC with Windows 11 OS with an Intel i3 core processor at 8 GB RAM and 2.10 GHz. The proposed TEADIS model was evaluated using segmentation metrics and network metrics. Figure No. 5 illustrates the outcomes of the TEADIS framework for tea leaf disease classification and segmentation.

Efficiency analysis based on field observation

In this section, the field observation data are evaluated using the proposed TEADIS framework. The Daily maximum and monthly average field observations from 2021 to 2023 are illustrated in Figure No. 6 and the probability distribution of field data is depicted in Figure No. 7.

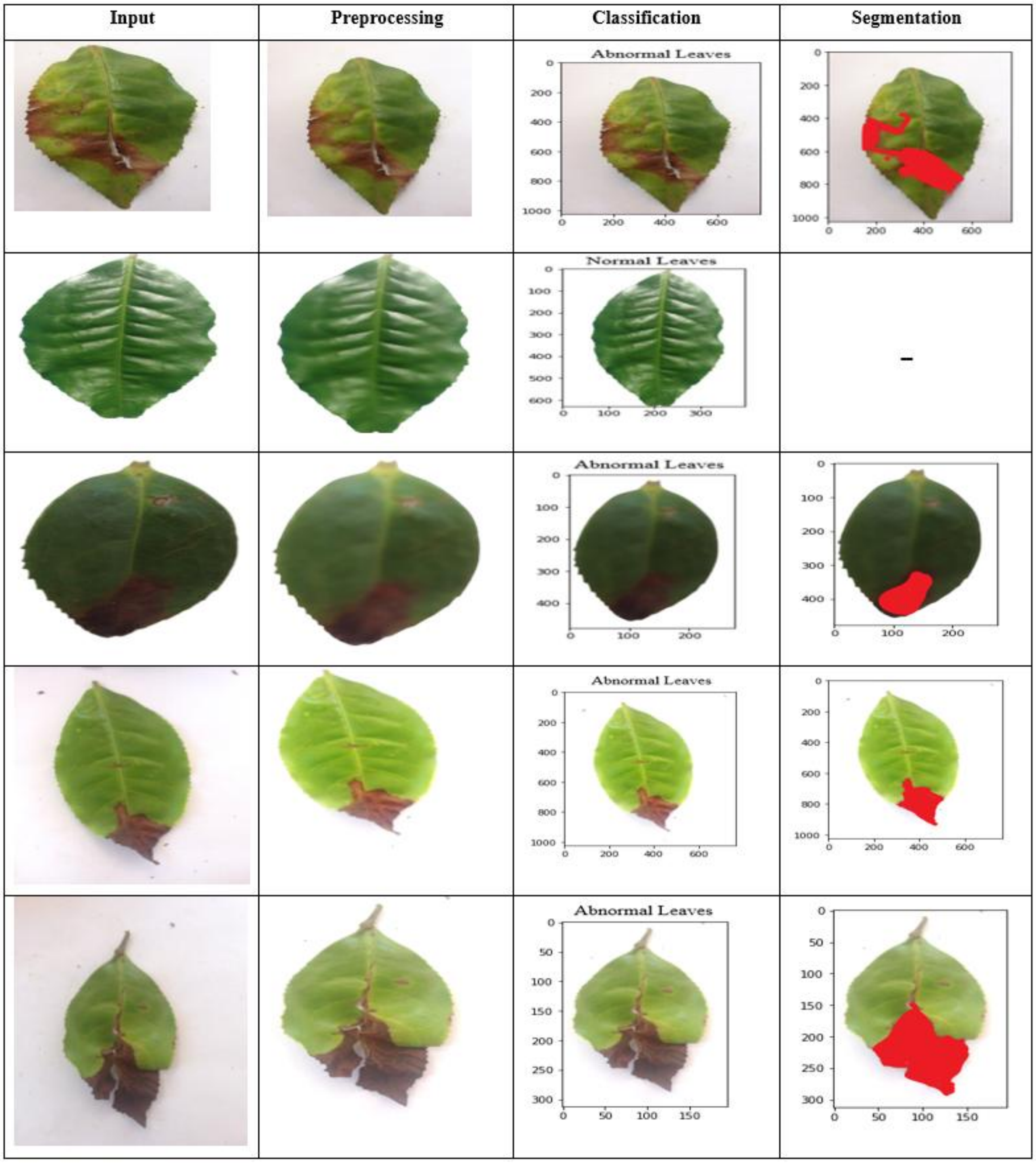


Figure No. 5
Experimental outcomes of the TEADIS framework

Figure No. 5 demonstrates the experimental result of the proposed TEADIS model with five different tea disease images. The tea leaves images from column 1 are gathered from a tea plantation in Ooty, Homewoodtea, India. The preprocessed images are illustrated in column 2. The classified images leaf (Normal and Abnormal) are depicted in column 3. The segmented tea leaf images are depicted in column 4.

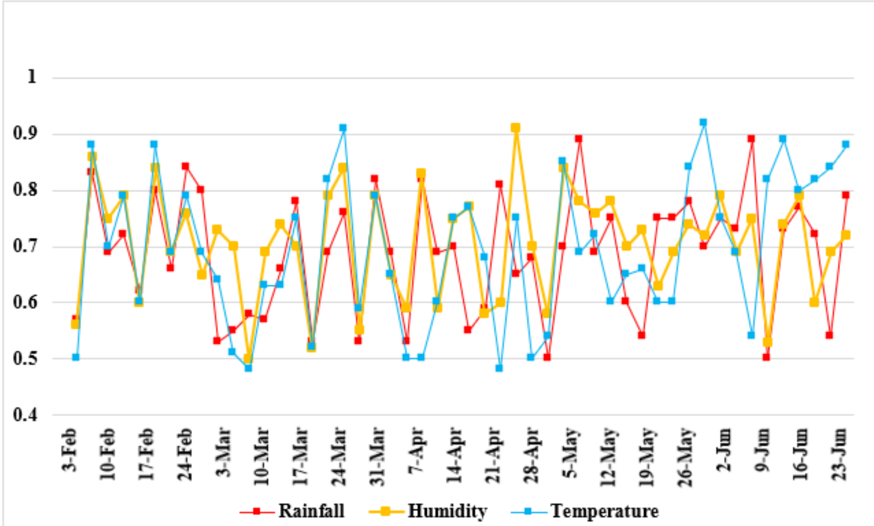


Figure No. 6
Field observation data from 2021 to 2023

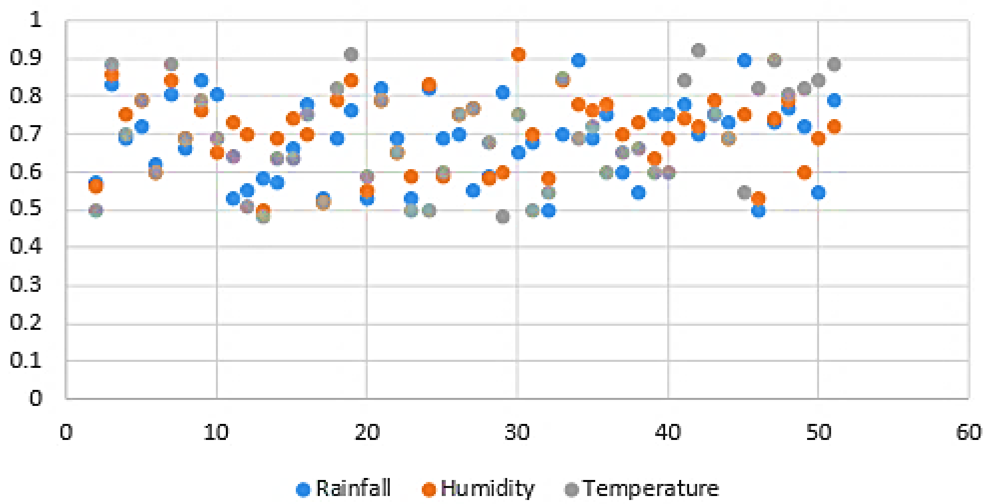


Figure No. 7
Probability distribution of field observation data

Figures No. 6 and No. 7 illustrate the field observation data such as temperature, rainfall, and humidity. During the growing season of the tea plant, the selected area's temperature is usually around 24°C, which promotes the spread of disease. The selected area experiences humidity ranging from 35 to 60% between February and June.

Table No. 2
Relation between disease severity and environmental factors

Diseases severity	Humidity	Rainfall	Temperature
	0.84	-0.44	0.81

The correlation between disease intensity and environmental factors is displayed in Table No. 2. There is a negative correlation between rainfall and the development of leaf disease, but a strong positive correlation with temperature and humidity.

Performance analysis based on DL technique

The efficiency of the TEADIS approach was examined using specificity, precision, recall, accuracy, and F1 score,

$$Specificity = \frac{T_{neg}}{T_{neg} + F_{pos}} \quad (11)$$

$$Precision = \frac{T_{pos}}{T_{pos} + F_{pos}} \quad (12)$$

$$Recall = \frac{T_{pos}}{T_{pos} + F_{neg}} \quad (13)$$

$$Accuracy = \frac{T_{pos} + T_{neg}}{Total\ no.of\ samples} \quad (14)$$

$$F1\ score = 2(\frac{Precision * Recall}{Precision + Recall} \quad (15)$$

The dice index (DI) is used to estimate the ratio of actual pixels to true regions. A Jaccard index (JI) determines the similarity between two samples by dividing their union and intersection.

$$DI = \frac{2T_{pos}}{F_{pos} + 2T_{pos} + F_{neg}} \quad (16)$$

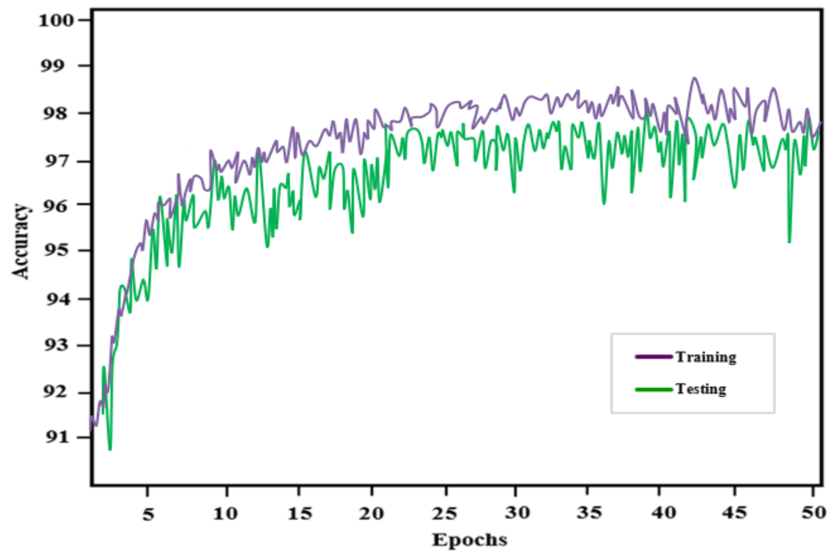
$$JI = \frac{T_{pos}}{T_{pos} + F_{neg} + F_{pos}} \quad (17)$$

Where T_{neg} and T_{pos} denotes the true negatives and true positives of the disease images, F_{neg} and F_{pos} denotes the false negatives and false positives of the disease images.

Table No. 3
Proposed TEADIS performance analysis

Images	Accuracy	Sensitivity	F1-score	Specificity	Precision	Dice index	Jaccard index
Normal	97.49	97.01	96.44	96.07	96.31	97.01	97.06
Abnormal	98.06	97.06	96.09	97.22	96.07	97.21	97.29
Average	97.77	97.03	96.26	96.64	96.19	97.11	97.17

Table No. 3 illustrates a performance analysis based on parameters specified for normal and abnormal images for the proposed TEADIS. The classification and segmentation performance is assessed using specificity, precision, recall, accuracy Jaccard index, Dice coefficient, and f1 score. The TEADIS framework attains 97.77% accuracy for the images collected from tea estates. Moreover, the TEADIS achieves the specificity, F1 score, precision, and recall of 96.64%, 97.03%, 96.26%, and 96.19%.



FigureNo. 8
Accuracy graph of the TEADIS technique

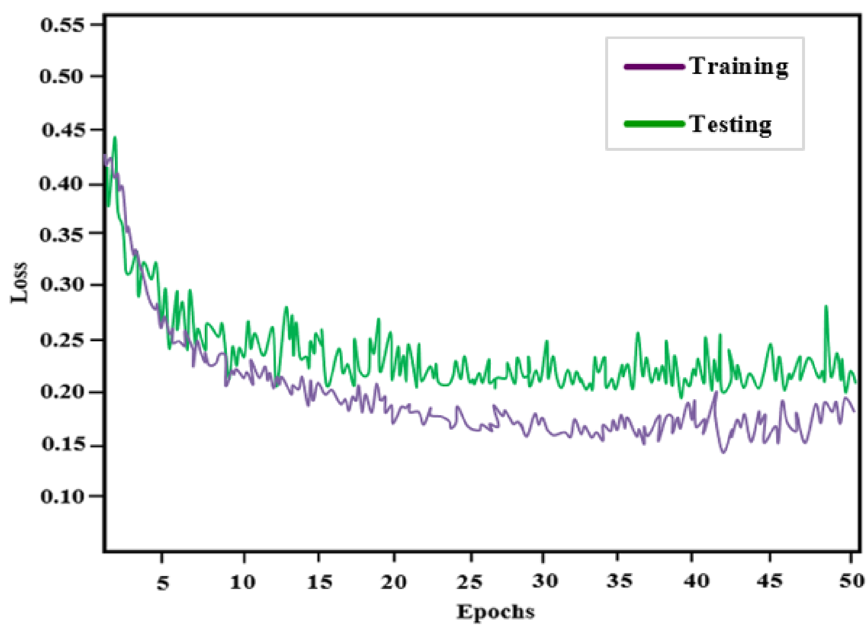


Figure No. 9
Loss graph of the TEADIS technique

Figure No. 8, illustrates the performance curve of the TEADIS model. The vertical axis illustrates the range of accuracy, and the horizontal axis illustrates the number of epochs. The performance of the TEADIS increases as the number of epochs increases. Figure No. 9, illustrates the loss curve of the TEADIS model. The loss of the TEADIS decreases as the epochs increase. The TEADIS model attains high accuracy for disease detection and segmentation.

Comparative analysis

In this comparative analysis section, the TEADIS model was compared with different traditional segmentation techniques based on different performance metrics. A comparative analysis of existing segmentation methods is presented in Figure No. 10.

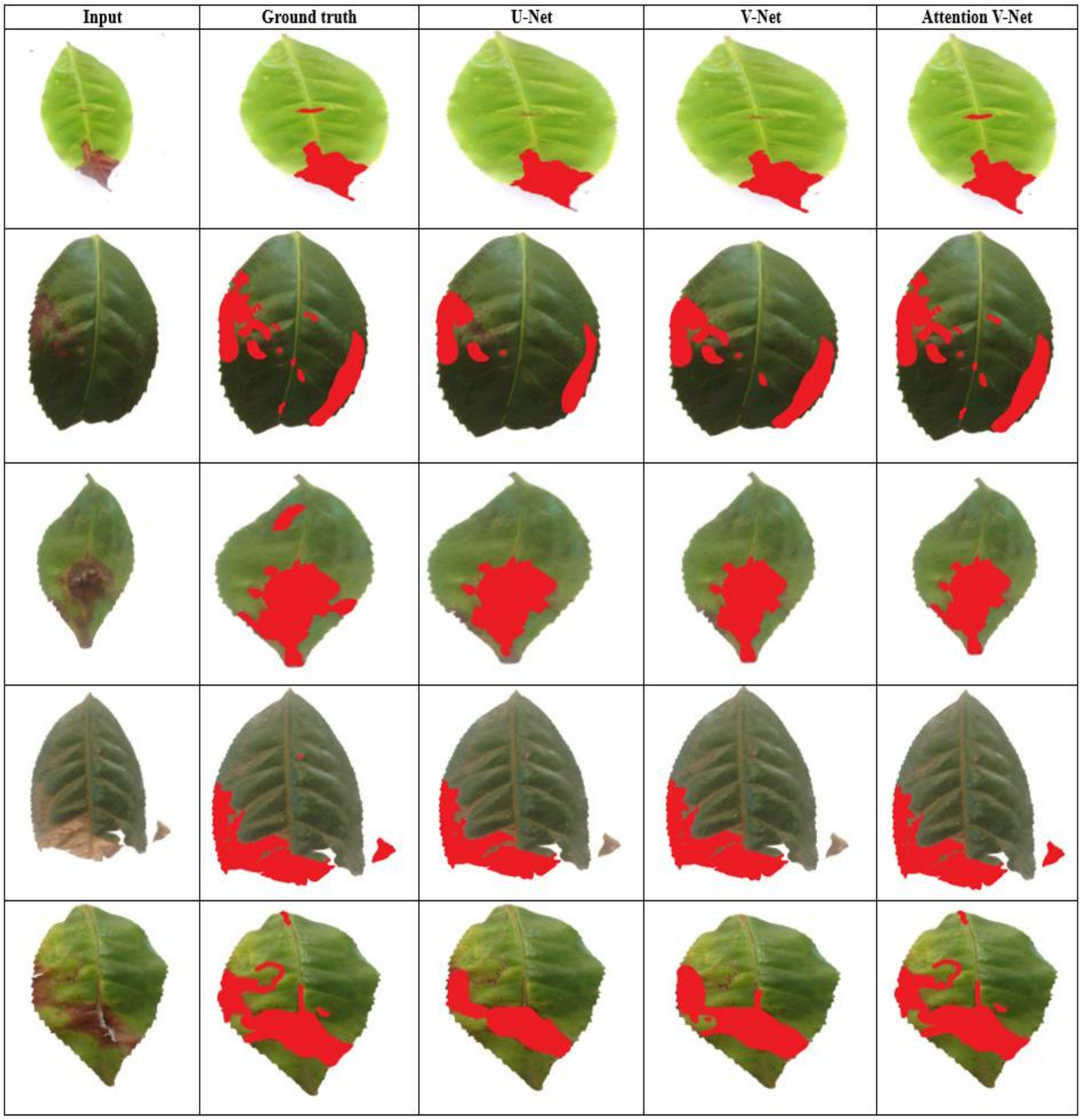


Figure No. 10
Segmented outcomes of TEADIS framework

Figure No. 10 illustrates the segmented outcome of the TEADIS model in which the proposed Attention v-net achieves better segmentation results based on the dice coefficient and Jaccard index. The jaccard index of Attention U-net is 0.84 which is almost equal to the ground truth value. Attention V-Net improves the system performance and minimizes the false positives, outperforming other models with a precise dice index of 0.89.

Table No. 4 illustrates the comparison of different traditional segmentation techniques based on efficiency metrics such as the dice coefficient and Jaccard index. Moreover, the proposed Attention V-net performs better when compared to the traditional segmentation techniques model. The Attention V-net attains the jaccard index of 0.05, and 0.03 better than Unet and V-net. The Attention V-net attains a dice coefficient of 0.08, and 0.05 better than Unet and V-net.

Table No. 4
Segmentation Techniques Comparison

Techniques	Dice coefficient	Jaccard index
V-net	0.84	0.81
U-net	0.81	0.79
Attention V-net	0.89	0.84

Table No. 5
Comparison of the tea disease's classification based on performance metrics

Methods	Accuracy	F1-score
AlexNet	90.4	89.9
VGG-16	91.4	90.8
Mobilenet	93.16	92.33
GoogLeNet	97.77	96.26

Table No. 5 illustrates the comparison of different DL-based classification techniques based on efficiency parameters including F1-score and Accuracy. Moreover, the GoogLeNet performs better when compared to the conventional classification approaches. The GoogLeNet increases the overall Accuracy by 7.53, 4.71, and 6.51 better than AlexNet, Mobilenet, and VGG. The GoogLeNet increases the overall F1-score by 6.60, 4.08, 5.67, better than AlexNet, Mobilenet and VGG.

Table No. 6
Accuracy Comparison

Researchers	Methods	Accuracy (%)
Bhagat & Kumar, 2024	Kernelized SVM	96.67%
Heng *et al*., 2024	WRF	92.47%.
Datta & Gupta, 2023	DNN	96.56%
Liu *et al*., 2022	ML & IoT	91%
Bhowmik *et al*., 2020	CNN	95.94%
Proposed	TEADIS	97.77%

Table No. 6 illustrates the efficiency comparison of the existing and proposed model for tea disease classification. In the GoogLeNet architecture, the learning rate is 0.001 to guarantee stable convergence during training. The learning rate for existing techniques such as WRF, DNN, ML & IoT, and CNN are 0.001, 0.0001, 0.001, 0.00001 whereas Kernelized SVM typically does not use a learning rate because they are not iterative optimization methods like neural networks. From this analysis, the proposed model has chosen the hyperparameters to balance the network's training speed and generalization capability. The proposed TEADIS achieves 97.77% of accuracy. The proposed TEADIS increases the accuracy range by 1.12%, 5.42%, 1.23%, 6.92%, and 1.87%, better than Kernelized SVM (Bhagat & Kumar, 2024), WRF (Heng *et al*., 2024), DNN (Jayapal & Poruran, 2023), ML & IoT (Lin *et al*., 2023), CNN (Nagasubramanian *et al*., 2021) respectively. The existing networks did not achieve improved outcomes when compared to the TEADIS network. Table No. 6 clearly shows that the TEADIS is superior to other methods. Therefore, the TEADIS is highly reliable for detecting dissimilar tea leaf diseases early.

DISCUSSION

The proposed TEADIS is introduced to categorize tea leaf diseases into normal and abnormal leaves using visual and digital data. Initially, the study calculated the number of training epochs required to reach the highest testing accuracy. The performance evaluation of the proposed model was calculated using certain parameters like specificity, accuracy, F1 score, precision, Jaccard index recall, and Dice index. The proposed TEADIS achieved 97.77% testing accuracy with a small error rate based on the 50 number of epochs from the Figure No. 8. The traditional DL networks did not attain improved outcomes when compared to the TEADIS based on GoogLeNet. The proposed TEADIS yields the best performance of 97.77%, which is comparatively better than the existing approaches based on the classification accuracy. Table No. 4 demonstrates proposed model attains better segmentation results based on Attention v-net when compared to existing segmentation techniques. As displayed in Table No. 6, the proposed TEADIS was superior to other latest methods. Therefore, in comparison to other existing approaches shown in Table No. 5, the proposed approach improves accuracy and reduces the computational cost with low training time. Therefore, the TEADIS MODEL is highly reliable for detecting tea leaf diseases in real time. However, the proposed framework lacks coverage for numerous tea leaf disease types. The limited number of training samples for different types of tea leaf disease has affected the performance of the TEADIS framework, which has been a major obstacle to achieving an automated tea leaf disease diagnosis system. In the future, the TEADIS aims to classify different types of diseases with more training sample images.

CONCLUSION

In this work, a novel DL-based TEADIS has been proposed to identify tea leaf diseases based on IoT. Initially, visual and digital data are gathered from the IoT devices and stored through Sigfox in the cloud environment. The visual data are pre-processed using a SCRAB filter to remove the noisy artifacts and enhance the edges of tea leaf images. The novel deep learning-based GoogLeNet with GeLu activation function is employed to classify the tea leaves into normal and abnormal leaves. The digital data from the environmental field are used to detect the occurrence of tea diseases for further segmentation. Finally, the proposed model utilizes Attention V-net to segment the affected region of the tea leaf images based on field observation. The TEADIS achieves an accuracy of 97.77%. In the future, TEADIS plans to classify different types of tea diseases and also provide fertilizer recommendations based on affected diseases.

Ethical approval

My research guide reviewed and ethically approved this manuscript for publishing in this Journal.

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