The Bioscan
AN INTERNATIONAL QUARTERLY JOURNAL OF LIFE SCIENCES
19(2): 156-160, 2024
www.thebioscan.com

Hibiscus Plant Leaf Disease Detection using Modified Sigmoid Function in Logistic Regression

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DOI: https://doi.org/10.63001/tbs.2024.v19.i02.pp156-160

KEYWORDS
Digital Images,
SVM classifier,
Logistic Regression,
RBF Kernel,
Hyperbolic Tangent function

Received on:
25-07-2024
Accepted on:
07-11-2024

ABSTRACT

Hibiscus plants are popular improvements known for their vibrant blooms and lush foliage. However, like all plants, they are disposed to various diseases that can poorly affect their health and aesthetics. As tropical plants, hibiscus plants need full sun to limited shade to thrive. Too much direct sunlight can result in leaf sunburn, causing little white spots to appear on the foliage. Early detection of these diseases is critical for timely participation and active management. In recent years, progressions in image processing and machine learning have offered promising solutions for mechanized disease detection in plants. This study proposes a novel approach for the automated detection of hibiscus plant leaf diseases using machine learning techniques. Digital images of hibiscus leaves are developed using a high-resolution camera or smartphone camera. Early detection and classification of diseases in hibiscus plants are dangerous for effective plant management and disease control. To evaluate the performance of proposed method, a dataset of labelled hibiscus leaf images containing different disease types. The extracted features are used to train a machine learning model to classify the images into healthy or diseased categories. For identification and classification of disease type, the existing method is SVM Classifier with "Modified RBF kernel" and the proposed method is "Logistic Regression with Modified Hyperbolic Tangent Function". The method's efficiency can be assessed by employing metrics such as accuracy, sensitivity, specificity, and F1 score. Future research directions include further optimization of the classification model and integration of additional image processing techniques aimed at improved performance in real-world applications.

INTRODUCTION

Hibiscus, commonly called Roselle, belongs to the family *Malvaceae*. Hibiscus has over 300 species of flowering plants, and one of them is *Hibiscus sabdariffa Linne* [1]. It is considered an adaptable plant that may have various health benefits. The potential uses and health benefits of hibiscus are Hypertension Management, Cholesterol reduction, Antioxidant Properties, Liver Health, Weight management, Digestive Health, Immune Support System, Skin Health, etc. For best growth, hibiscus plants, being tropical in nature, require exposure to either full sun or partial shade. Too much direct sunlight can result in leaf sunburn, causing little white spots to appear on the foliage. However, too little light will not allow the plant to produce sufficient chlorophyll to keep the foliage green. Hibiscus are full-sun plants. Lack of sunlight can cause overall yellowing of the leaves. On the other hand, if the plant is getting sunburned, the leaves can get yellow or white splotches.The early detection and necessary action to prevent leaf disease are of utmost importance. Since plants grow in an unrestrained external surrounding, chances of infection are more. There is a need for detection of the disease-causing insects, the impact of the disease, and how it manifests. Logistic regression is one of the most popular Machine Learning algorithms [2], which comes under the Supervised Learning technique [3]. It is used for predicting the categorical dependent variable using a given set of independent variables. Logistic regression [4] predicts the output of a categorical dependent variable. Therefore, the outcome must be a categorical or distinct value. It can be either Yes or No, 0 or 1, true or False, etc. but instead of giving the exact value as 0 or 1, it gives the probabilistic values which lie between 0 and 1. The significance of addressing hibiscus leaf disease lies in the economic and ecological value of hibiscus plants. Hibiscus, honored for its vibrant blooms and diverse applications, holds cultural significance and plays a crucial role in industries such as horticulture, herbal medicine, and ornamental gardening. The presence of hibiscus leaf diseases threatens plant health and productivity, affecting livelihoods and biodiversity [5]. Thus, there is an urgent necessity to comprehend, control, and improve the difficulties linked with hibiscus leaf diseases. Hibiscus leaf diseases, including fungal, bacterial, and viral infections, as well as physiological issues, harm the leaves and health of hibiscus plants. Symptoms like leaf discoloration, lesions, deformities, and early leaf shedding lead to weaker growth and fewer flowers. If not allocated with, these diseases can cause big financial losses for growers, spoil the beauty of landscapes, and interrupt natural ecosystems. Despite available solutions like cultural practices, chemicals, and impervious varieties, managing hibiscus leaf diseases is still tough and intricate. Several challenges complicate the management of hibiscus leaf diseases like Pathogen Diversity, Environmental Factors, Resistance Development, Diagnostic Challenges, Integrated Management Approaches. To tackle these challenges, to create new and inclusive methods for efficiently controlling hibiscus leaf diseases.

Challenges in hibiscus plant leaf disease:

Detecting and dealing diseases in hibiscus plants carriage several challenges to growers and researchers alike:

- **Diverse Range of Diseases:** Hibiscus plants are vulnerable to numerous diseases caused by fungi, bacteria, viruses, and environmental factors [6]. Categorizing and distinguishing between different diseases can be stimulating due to overlying symptoms and disease development.
- **Symptom Variation:** Disease symptoms in hibiscus plants can manifest differently liable on factors such as the type of pathogen, environmental surroundings, and plant health. This inconsistency makes precise diagnosis and disease management more difficult.
- **Limited Resistance:** While some hibiscus varieties show resistance to certain diseases, many cultivars are vulnerable to a wide range of pathogens. Limited availability of resistant cultivars increases the reliance on chemical treatments for disease control.
- **Environmental Factors:** Environmental conditions such as temperature, moisture, and rainfall can impact the frequency and brutality of hibiscus plant diseases. Predicting disease outbreaks and managing them efficiently require understanding the complex connections between pathogens and environmental factors.
- **Diagnostic Challenges:** Categorizing the underlying agent of a disease in hibiscus plants often requires laboratory analysis, including microscopy, culture, and molecular techniques. However, these diagnostic methods can be time-consuming, exclusive, and may not always yield definitive results.
- **IntegratedManagement Approaches:** Implementing effective disease management policies for hibiscus plants requires an integrated approach that syndicates cultural practices, chemical treatments, biological controls, and resistant cultivars. Organizing these approaches and optimizing their effectiveness can be challenging.
- **Invasive Pests:** In addition to diseases, hibiscus plants are also susceptible to damage from offensive pests such as aphids, whiteflies, and thrips. Controlling pest populations and preventing their spread further complicates hibiscus plant health management.
- **Market Demands and Aesthetics:** Hibiscus plants are often grown for attractive purposes, and their esthetic value is vital to growers and landscapers. Managing diseases while sustaining the pictorial appeal of hibiscus plants poses an additional challenge.

Addressing these challenges requires ongoing research, association between researchers and growers, and the development of innovative disease management strategies personalized to the exclusive characteristics of hibiscus plants and their growing environments.

LITERATURE SURVEY:

Smita Unnikrishnan [7] et al.2021 research explores the efficient detection of plant diseases using machine learning (ML) techniques. It traces the evolution of disease identification methods, from rule-based systems to ML, highlighting supervised learning models like support vector machines (SVM) and random forests. With the initiation of deep learning, convolutional neural networks (CNNs) have become powerful tools, transforming disease identification. Extensive datasets have been curated, addressing challenges such as class inequity and lighting variations. Recent advancements include ensemble methods, fine-tuning, and explainable AI techniques. Future research directions encompass multispectral imaging, edge AI, and transfer learning across plant species. Overall, the paper contributes to enhancing agriculture and food security by leveraging ML for plant disease detection.

Ravi Ranjan Kumar [8] et al.2023 conducted a study focusing on proposing a novel method for identifying diseases in hibiscus plants by combining Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). The research addresses the urgent concern of plant diseases leading to substantial agricultural losses. Their hybrid approach involves utilizing CNNs for feature extraction from leaf images and SVMs for classification. The methodology encompasses image preprocessing, CNN-based feature extraction, and SVM-based classification. The study likely evaluates the method's efficacy using metrics such as accuracy, precision, recall, and F1-score. In conclusion, the proposed approach holds promise for justifying disease detection in hibiscus plants, potentially assisting farmers in safeguarding crop yields.

Sandip Kumar Roy [9] et al.2023 conducted a study focusing on which explores the application of deep learning techniques for detecting diseases in hibiscus plants through image analysis. The research presents a method that utilizes deep learning algorithms to analyse images of hibiscus leaves and accurately identify signs of disease. By manipulating deep learning models, the system can automatically learn and extract relevant features from the images, facilitating robust disease detection. This approach shows promise in providing an efficient and reliable solution to the challenge of early disease detection in hibiscus plants, hypothetically supporting farmers in effectively managing plant health and enhancing crop yields.

Yash Dusane [10] et al.2024 conducted a study focusing on which aimed to develop a classification system for identifying diseases in hibiscus plant leaves. The research likely exploited various machine learning or deep learning techniques to analyse images of hibiscus leaves and classify them based on the presence or absence of diseases. The study aimed to provide an automated solution for early disease detection, smoothing timely management and treatment of plant health issues. By implementing this classification system, farmers could theoretically monitor the health of their hibiscus plants more effectively, leading to improved crop yields.

Hamada F. A. Ahmed [11] et al.2023 conducted a study focusing on the application of biotic and abiotic inducers to stimulate universal resistance in Hibiscus sabdariffa Linn. plants as a means of managing root rot and wilt diseases. The study likely explores various inducers, including beneficial microbes or plant extracts, and evaluates their effectiveness in enhancing the plant's innate defence mechanisms against these diseases. Experimental methodologies for inducing systemic resistance, as well as assessments of disease incidence and strictness, and measurements of plant growth parameters, are probably detailed. Additionally, the article likely discusses the potential applications of induced systemic resistance as an eco-friendly and workable strategy for disease control in hibiscus cultivation. Overall, this research offers valuable insights into innovative approaches for disease management in hibiscus plants, with the ultimate goal of enhancing crop health and yield.

Sumaya Mustofa [12] et al.2023 study provides a comprehensive analysis of deep learning techniques utilized for the detection of plant leaf diseases. The review likely involves various aspects of the subject, including challenges associated with traditional disease detection methods, the benefits of retaining deep learning, and recent advancements in the field. It probably discusses different deep learning architectures and algorithms utilized for plant leaf disease detection, along with their respective advantages and limitations. Furthermore, the review may underscore the significance of large and diverse datasets in effectively training deep learning models. Additionally, it could explore probable applications of deep learning in agriculture, such as precision agriculture and disease management. Overall, the review serves as a comprehensive reference for researchers and practitioners interested in harnessing deep learning for the detection of plant leaf diseases.

M. Meena [13] et al.2022 paper, investigates how deep learning can enhance the detection of plant diseases, a vital aspect for agricultural sustainability. It explores various deep learning models like CNNs and RNNs, highlighting their efficacy in analysing plant images for disease identification. The review encompasses discussions on datasets used, preprocessing techniques, model performance evaluation, and challenges encountered in disease detection. Overall, it underscores the potential of deep learning to develop agriculture by enabling early and precise disease identification, ultimately benefiting crop yields and food security.

Sapna Nigam [14] et al.2020 provides an in-depth exploration of how deep learning techniques are transforming the field of plant disease identification. It discusses the shift from traditional methods to deep learning, particularly emphasizing the effectiveness of convolutional neural networks (CNNs) in analyzing image data for disease detection. The review also covers the importance of datasets, earlier models like support vector machines (SVM), and recent advancements such as ensemble methods and explainable AI. It concludes by outlining future research directions. Overall, the paper serves as a valuable guide for researchers and practitioners in agriculture, offering insights into cutting-edge methods for plant disease detection.

Bhimavarapu Usharani [15] et al.2023 focuses on using machine learning to identify and classify diseases in houseplant leaves. The study addresses the need for technology in managing indoor plant health. The authors explain how they collect and prepare leaf images, train machine learning models, and evaluate their performance. The paper stresses the importance of accurate disease detection for timely plant care. Overall, it offers useful guidance for plant lovers, researchers, and developers interested in using technology to monitor indoor plant health.

M. Kiruba Devi [16] et al.2023 explores how to notice diseases in plant leaves, highlighting the importance of early detection for healthy crops. Devi confers using image processing and machine learning to identify and diagnose these diseases. The paper covers image acquisition, preprocessing, feature extraction, and classification techniques. It highlights the significance of precise disease identification for better agricultural management and suggests the probable of computer vision and machine learning for powering detection. Overall, the paper is a valuable resource for researchers, agricultural professionals, and technologists aiming to use technology to improve crop health.

PROPOSED METHOD:

The process of identifying diseases in plant leaves using an automatic disease identification system consists of five main stages. These stages include image capture, initial processing, dividing the image into distinct parts, extracting important characteristics, and categorizing the disease. These steps are essential components in creating a system for detecting leaf diseases using image processing methods.

1. *Image Acquisition*: Image acquisition refers to the process of obtaining an image of leaf from various sources, typically utilizing hardware components like cameras, sensors, or encoders.
2. *Pre-processing:* Image pre-processing involves basic operations on leaf images to improve data quality, such as noise reduction and feature enhancement [17], essential for subsequent analysis tasks.
3. *Segmentation*: Segmentation partitions digital images into discrete segments to aid in object detection, utilizing techniques from experiential analysis. It finds applications in medical imaging, robotics, autonomous vehicles, and satellite image analysis.
4. *Feature Extraction*: Feature extraction is the process of condensing raw data into manageable groups, easing computational demands by selecting and combining variables into descriptive features, thus reducing data volume while retaining accuracy and originality.

Image enhancement [18] is a critical component within image-centric applications, with its primary objective being the refinement of images to enhance quality, visual perception, and suitability for subsequent processing techniques such as [19] segmentation, feature extraction, and classification. The development of image enhancement techniques prioritizes speed, efficiency in noise reduction, and the facilitation of accurate segmentation. During the acquisition of leaf images, factors such as environmental conditions or camera sensor settings can lead to the capture of images with diminished intensity or inadequate contrast. Contrast, crucial for object discernibility, denotes the variation in intensity or colour within an image. From the perspective of human visual perception, contrast is gauged by observing disparities in both colour and brightness between an object and its surroundings within the viewing area. It can be quantified as the variation between the brightness levels of the darkest and lightest pixels within an image.

Poor illumination or inadequate lighting during image or video capture can result in diminished contrast, leading to visual quality issues that hinder information recognition. To address this, various techniques have been introduced to enhance contrast in low-contrast or poorly illuminated images. Contrast enhancement not only improves visual perception but also enhances overall image quality. The refined images produced through contrast enhancement are better suited for subsequent processing tasks such as segmentation, analysis, classification, and recognition. These enhancement techniques can be broadly categorized into two groups: direct methods, which operate directly on the pixel intensity values of the image, and indirect methods, which operate in the frequency domain.

Logistic regression:

- Logistic regression, a fundamental tool in the field of machine learning, assists as a robust algorithm mostly employed in classification tasks. Unlike linear regression, which deals with predicting continuous values, logistic regression specializes in estimating the probability of an instance fitting to a specific class.
- This algorithm is personalized for predicting clear-cut outcomes, thus demanding the dependent variable to be of a discrete nature, such as binary choices like Yes or No, 0 or 1, or true or false. Instead of yielding exact categorical values, logistic regression provides probabilistic scores ranging between 0 and 1.
- Conflicting to linear regression [20], which addresses regression problems, logistic regression finds its position in solving classification tasks. It employs an "S"-shaped logistic function rather than fitting a regression line, empowering the prediction of binary outcomes with two potential maximum values (0 or 1).
- The curve produced by the logistic function offers perceptions into the possibility of various scenarios, such as determining the presence of cancerous cells or assessing obesity based on a mouse's weight.
- With its ability to provide prospects and classify new data using both continuous and distinct datasets, logistic regression holds significant importance in the empire of machine learning.
- Moreover, logistic regression simplifies the classification of observations across various data types and enables the proof of identity of the most significant variables for classification tasks. The logistic function, described below, visually summarizes the essence of logistic regression.

Role of sigmoid function in logistic regression:

The sigmoid function [21], also known as the logistic function, is a mathematical curve that has an S-shaped or sigmoidal curve. It is well-defined as follows

$$S(x) = \frac{1}{1+e^{-x}}$$

In this equation:

- $f(x)$ signifies the output of the sigmoid function.
- x is the input, which can take any real value.
- e is the base of the normal logarithm, almost equal to 2.71828.

The sigmoid function takes any real number as input and outputs a value between 0 and 1. It slants 0 as the input becomes negative and 1 as the input becomes positive. When the input is 0, the sigmoid function returns 0.5.

Hyperbolic tangent function:

The hyperbolic tangent function, commonly denoted as tanh(x), is a mathematical function widely employed in artificial neural networks [22] and machine learning algorithms. It maps any real number input to a value between -1 and 1, making it a valuable

tool for introducing non-linearity in neural network architectures [23].
The formula for tanh(x) is derived from the definitions of hyperbolic sine (sinh(x)) and hyperbolic cosine (cosh(x)):

$$\sinh(x) = \frac{e^x - e^{-x}}{2}$$

$$\cosh(x) = \frac{e^x + e^{-x}}{2}$$

By expressing tanh(x) as the ratio of sinh(x) to cosh(x), we arrive at the equation:

$$\tanh(x) = \frac{\sinh(x)}{\cosh(x)}$$

Substituting the expressions for sinh(x) and cosh(x) into this equation, we simplify to obtain:

$$\tanh(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})}$$

Thus, tanh(x) is defined as the hyperbolic tangent of x, expressed as the difference of exponentials divided by their sum. This definition showcases its zero-centered nature and its ability to map real numbers to values within the interval [-1, 1].

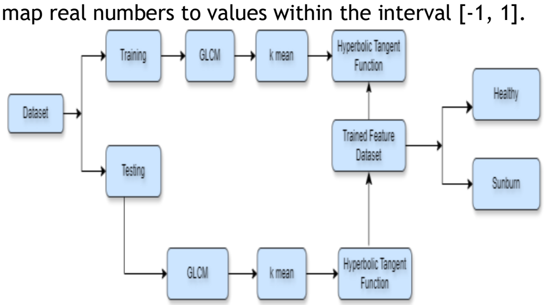

Figure 1: Flow Diagram for Proposed Methodology

RESULT ANALYSIS AND DISCUSSION:

Leaf Image Dataset:

This study requires access to a comprehensive and varied dataset, pivotal for assessing the proposed methodology. The selected dataset forms the cornerstone for evaluating the proposed approach. Employed in this study is the hibiscus leaf disease dataset, a segment of the Plant Village repository, comprising 54,306 images depicting diseased leaves across 26 distinct plant species. Within this collection are 2,475 samples of hibiscus plant leaves, encompassing both healthy and diseased states. Of these, 997 samples are designated as healthy, while 1,478 exhibit bacterial spots. A total of 1,980 instances are utilized for training purposes, with only 495 reserved for evaluating the model's performance. The dataset can be accessed via the following URL:https://www.kaggle.com/datasets/sayooj98/hibiscus-leaf-dataset-small

Evaluation Metrics:
The performance evaluation conducted in this research involved a meticulous analysis of various metrics to gauge the effectiveness of the proposed methodology compared to existing approaches. In addition to accuracy, precision, recall, F1 score, and false positive rate (FPR) were employed to provide a comprehensive assessment of model performance. These metrics offer insights into different aspects of the model's performance, such as its ability to make correct positive identifications, avoid false positives, capture all positive instances, and minimize false negatives. By utilizing a diverse set of evaluation metrics, we ensure a thorough and unbiased evaluation of the proposed methodology, enabling a fair comparison with existing works.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{F1 Score} = \frac{2*\text{precision}*\text{recall}}{(\text{precision}+\text{recall})}$$

$$\text{FPR} = \frac{FP}{TN+FP}$$

Table 1: Contrast of Accuracy between the existing approach and the proposed approach.

Training and Testing Ratios	Existing[12]	Proposed
80: 20	85.00	85.41
70: 30	85.00	77.37
60: 40	85.00	90.97
50: 50	85.00	91.66

In the existing work, precision,Recall,F1 score,FPR was not computed as part of the analysis. However, in the proposed methodology, we included as a crucial evaluation metric. These metrics which measures the accuracy of positive predictions made by the model, provides valuable insights into the performance of the proposed approach. By incorporating these metrics into the evaluation process, this work gain a more comprehensive understanding of the model's effectiveness in correctly identifying relevant instances within the dataset. This enhancement enables a more robust assessment of the proposed methodology's efficacy in comparison to the existing approach.

Table 2 : performance metrics for the proposed method

Training and Testing Ratios	Precision	Recall	F1	FPR
80 : 20	0.88	0.85	0.86	0.14
70 : 30	0.85	0.77	0.82	0.02
60 : 40	0.91	0.90	0.91	0.08
50 : 50	0.92	0.91	0.91	0.08

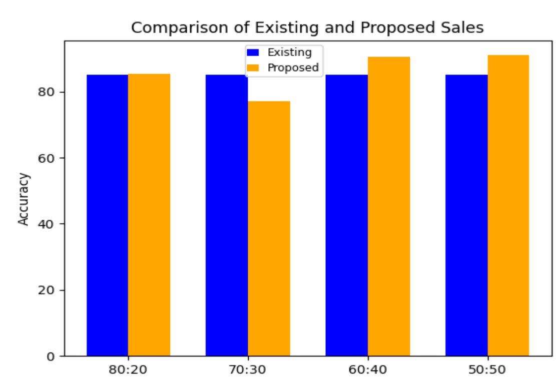

Figure 2: Accuracy comparison of proposed method and existing method

CONCLUSION

In conclusion, this research presents a probable solution for hibiscus plant leaf disease. The integration of GLCM [24] and the

SVM classifier [25] with modified RBF kernel [26] model establishes the potential of innovative image processing techniques and machine learning in lecturing agricultural challenges. The proposed logistic regression with a modified hyperbolic tangent function outstrips over the existing SVM classifier with a modified RBF kernel offer in terms of performance calculation metrics. By enabling timely disease identification, the proposed approach provides to improve crop management.

The proposed approach constantly outperforms the existing approach across different training and testing ratios. In most of the situations, the proposed method achieves higher accuracy compared to the existing method.

At a training and testing ratio of 80:20, both approaches yield the same accuracy of 85.41%. However, as the training dataset quantity decreases and the testing dataset percentage increases, the performance of the existing approach diminishes, while the proposed approach preserves or improves its accuracy.

At a 70:30 ratio, the proposed approach achieves an accuracy of 77.37%, which is lower than the existing approach's accuracy of 85.00%. However, beyond this point, the proposed method demonstrates greater performance. At ratios of 60:40 and 50:50, the proposed approach attains accuracies of 90.97% and 91.66%, respectively, outstanding the accuracy of the existing approach at those ratios.

This trend specifies that the proposed methodology, employing Logistic Regression with Modified Hyperbolic Tangent Function, exhibits robustness and effectiveness in classifying hibiscus leaf diseases compared to the existing method, SVM Classifier with Modified RBF kernel. The higher accuracies accomplished by the proposed approach across various training and testing ratios suggest its probable for accurate and consistent disease detection in hibiscus plants.

FUTURE SCOPE:

In the future, there are numerous areas where enhancements and examination can increase the efficiency of disease detection in hibiscus plants. Firstly, testing the model on a wider dataset containing various hibiscus leaf images with various diseases and environmental conditions will help evaluate its adaptability. Further experimentation with different training and testing ratios can optimize model performance. Exploring advanced feature extraction techniques personalized for hibiscus leaf disease detection, along with hyperparameter tuning, can enhance the model's accuracy and robustness. Integration of ensemble learning methods and transfer learning from pre-trained convolutional neural networks could further improve disease detection capabilities. Developing a real-time disease detection system for smartphone use, designing user-friendly interfaces, and conducting longitudinal studies for continuous nursing are also important paths for future research. Association with experts and data sharing creativities can improve research efforts in this field.

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