

Deep HybridNet with hybrid optimization for enhanced medicinal plant identification and classification

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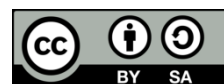
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ABSTRACT

Herbal leaves, known for their efficacy in treating a range of infectious diseases including cancer, asthma, and heart conditions, are still widely used by medical professionals. Traditionally, villagers have identified these plants visually, but given the similarity in appearance among various species, this method is prone to human error. Accurate identification of these plant species is critical for effective treatment. Hence, the development of an intelligent plant classification system is crucial to reduce the risk of misidentification and enhance treatment accuracy. This paper introduces the deep HybridNet with hybrid optimization module (DeepHybrid-OptNet) a novel deep learning framework for medicinal plant identification and classification. Merging convolutional and recurrent neural network architectures, deep HybridNet excels in extracting complex botanical features through channel-wise feature extraction modules in convolutional neural network (CNN) and feedback loop in recurrent neural network (RNN). The incorporation of a DeepHybrid-OptNet module enhances the model's learning efficiency and accuracy. Empirical results on the Mendley and folio dataset demonstrate the framework's superiority over existing methods in accuracy, precision, and recall making it a valuable asset for botany and herbal medicine research.

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1. INTRODUCTION

Plants, being a vital component of our ecosystem, also function as a valuable reservoir of organic compounds and pharmaceutical bodies. Plants have traditionally been utilized as medicinal resources by individuals globally for a significant period. Based on the findings presented in the State of Plants report [1], it is widely acknowledged within the scientific community that there are approximately 390,000 distinct plant species. The identification and classification of each of these species pose a substantial challenge for botanists and other specialists. This holds especially true for individuals lacking specialized knowledge or expertise in the given subject matter. To effectively classify plant species that share similar traits and have few distinguishing features, it is essential to utilize a precise categorization method. A thorough comprehension of a plant can be obtained through the examination of its leaves, as they possess ample information regarding the plant's characteristics. Throughout history, humans have consistently employed

plants for a diverse array of purposes, and there is no indication that this practice will diminish in the foreseeable future. The list includes purposes such as food, medicine, shelter, and other essential requirements [2].

Medicinal plants have been employed in traditional medical practices for a considerable duration owing to their nutritional value and therapeutic properties [3]. The antibacterial, anti-allergic, anti-inflammatory, and antioxidant properties of these substances are attributed to the presence of bioactive chemicals, including anthocyanin, carotenoid, and phenolic compounds. A wide range of plant species, encompassing trees, shrubs, and herbs, have been recognized for their therapeutic attributes. The singular distribution of a species is contingent upon the habitat to which it has adapted over some time. According to data [4], an analysis has revealed that an estimated 14% to 28% of plant species exhibit medicinal properties. Furthermore, the utilization of medicinal plants is widespread among diverse populations. In affluent countries, an estimated 3% to 5% of patients depend on these botanical specimens for their therapeutic benefits. In the context of developing nations, the percentage of individuals without access to basic amenities increases notably, reaching over 80% within rural populations. In the Southern Sahara region, approximately 85% of individuals rely on medicinal plants to treat their ailments. Moreover, considering the detrimental impacts and potential hazards linked to chemical medications, a subset of individuals residing in developed nations have opted to employ traditional remedies sourced from medicinal plants as a means of managing and addressing various illnesses and disorders [5]. The aforementioned plants exhibit medicinal properties as well as practical uses in culinary, beverage, and cosmetic applications. Regrettably, a prevalent problem exists in the global manufacturing and distribution of medicinal plants, where there is a significant presence of substandard, compromised, or improperly stored products. This situation poses potential risks to consumers [6].

Machine learning techniques have been effectively employed to carry out classification tasks with enhanced accuracy. The primary objective is to acquire a sufficient quantity of photographs of the merchandise for further processing. The methodology outlined entails the extraction of distinct characteristics of a product, including dimensions, consistency, and shape. The purpose of this isolation is to facilitate the classification of the product. One of the key advantages of machine learning is its capacity to efficiently analyze large volumes of data [7]. The utilization of machine learning (ML) techniques has been extensively employed to enhance the outcomes in rice categorization. The aforementioned techniques possess the ability to extract a wide range of physical characteristics from specific data. Deep learning (DL) is a subfield of machine learning (ML) that utilizes artificial neural networks (ANN) to enhance learning capabilities and optimize performance in various tasks, including object and image detection [8]. The intricate structure of deep learning algorithms can be attributed to their requirement for significant quantities of training data and advanced computational resources.

The utilization of deep learning models has shown considerable promise in the segmentation and classification of plant leaf diseases. To optimize their effectiveness and utility, it is imperative to address specific concerns. One of the challenges that must be addressed is the improvement of precision. The categorization of plants is a computer vision challenge that has been successfully tackled using deep learning methods, specifically by employing convolutional neural networks (CNNs) [9]. Deep learning obviates the necessity of rigorous feature extraction and domain expertise, which has conventionally been exclusive to proficient botanists. The process involves extracting discriminative patterns from individual plant leaves through a sequence of convolution operations performed between the input image and convolutional filters. The outcome of this process is the generation of a feature map. A plethora of deep learning-based image identification techniques and applications are readily available and continue to garner significant attention. Various methodologies can be utilized to tackle computational obstacles in the fields of botany and agriculture [10].

The primary motivation behind this comprehensive study lies in the quest to harness the remarkable potential of machine learning and deep learning techniques to revolutionize the field of botany, specifically in the identification and classification of medicinal plants. Given the vast diversity of plant species, with estimates suggesting around 390,000 distinct types, and the critical role they play in traditional and modern medicine, there is a persistent need for accurate, efficient, and automated systems to aid in their identification and classification. This is especially crucial considering the reliance of a significant portion of the world's population on medicinal plants for healthcare, particularly in developing countries and rural areas. This study not only seeks to enhance the accuracy and efficiency of plant classification but also aspires to mitigate risks associated with misidentification, thereby ensuring safer and more effective use of medicinal plants across various applications.

- Development of deep HybridNet with hybrid optimization module (DeepHybrid-OptNet): The study introduces an innovative deep learning framework, DeepHybrid-OptNet, designed specifically for the accurate identification and classification of medicinal plants. This framework combines convolutional and recurrent neural network architectures, excelling in extracting complex botanical features.

- Incorporation of a hybrid optimization module: the model integrates a hybrid optimization module, which enhances the model's learning efficiency and accuracy. This aspect of the model contributes significantly to its overall performance in classification tasks.
- Empirical evaluation and superior performance: the research provides empirical results demonstrating the framework's superiority over existing methods in terms of precision and speed.

The research organization is segmented into 4 sections in this paper, the first section gives a brief overview by discussing the importance of plant species, especially medicinal plants, their uses, and the challenges in their identification and classification. The second section focuses on the existing research, focusing on the use of deep learning methods in plant identification, and outlines the limitations and gaps in current methodologies. The third section discusses the proposed methodology and architecture. The fourth section discusses the results and analysis obtained.

2. RELATED WORK

The increasing effectiveness of deep learning methods in accurately identifying and classifying plant leaf diseases has been increasingly recognized in recent years. Various studies have been conducted to assess the effectiveness of different deep learning architectures, such as MobileNet, visual geometry group (VGG16), and various U-Net variants, to identify and categorize plant leaf diseases. This section presents a comprehensive review of relevant studies on the topic and evaluates the merits and limitations of various methodologies [11]. The objective of this study is to integrate artificial neural networks (ANN) and support vector machines (SVM) to perform feature extraction and classification. This will be achieved by leveraging pre-trained models and employing the transfer learning technique [12]. The Bayesian optimization approach is employed to meticulously adjust the hyperparameters of the SVM to enhance the performance of the model. The DeepHerb model is utilized by the HerbSnap smartphone application to effectively identify and assess key attributes of herbs stored in its diverse platform database. The establishment of a connection enables the program to generate herb images with a latency of one second [13].

Sapna *et al.* [14] presents a comprehensive guide on constructing a machine learning model capable of accurately classifying medicinal plants. To facilitate the training and evaluation of the model, a comprehensive compilation of diverse medicinal plant specimens was generated. The deep CNN architecture was trained and improved using a dataset of medicinal plants. The significance of this stage in the model-building procedure has been firmly established. The utilization of data augmentation techniques resulted in improved durability and generalization capabilities of the model. The advancement of plant species identification has made significant progress since the inception of computers and other technological innovations. A comprehensive investigation was conducted to classify plant species based on an analysis of their leaf characteristics. However, there is currently no available information regarding the automated identification of other components within plants. The objective of this study is to investigate the precise and automated recognition of flowers from medicinal plants within their native environment. In [15], the process involves the consolidation of four distinct classifications of commonly found medicinal plant species in the Philippines. This consolidation results in the creation of a new dataset specifically designed for the identification of medicinal plants. A model based on you only look once-5 (YOLOv5) was trained to accurately detect and classify blooming medicinal plants.

The process of manually locating and identifying plants is a demanding and time-consuming task. The application of machine learning offers a more advantageous and promising methodology. Machine learning algorithms are currently employed to analyze photographs of diseased plants to identify the plants and analyze their phenotypic characteristics. The achievement of this capability is facilitated by the algorithms' efficient collection, arrangement, and retention of vast quantities of data. The primary objective of this research study is to explore the potential application of machine learning techniques in the identification of plant leaves possessing favorable anti-diabetic properties. In this particular case, machine learning approaches are utilized to identify and categorize the leaves of various anti-diabetic plants. The plant species encompassed in this list are *Hibiscus rosa-sinensis*, *Fenugreek*, *Psidium guajava*, *Basella alba*, and *Moringa oleifera* [16].

The current process of identifying medicinal plants relies [17] on the transmission of knowledge from one generation to another and the expertise of specialized professionals. Misidentification of botanicals utilized in Ayurveda remedies can lead to unforeseen, distressing, and challenging-to-address consequences. Hence, the Ayurvedic healthcare business requires an automated system that can effectively classify plant species by analyzing their leaf characteristics. The automated system should incorporate advanced technologies such as computer vision and machine learning. The present study utilizes a dataset that was generated internally, comprising 4,390 images of medicinal leaves sourced from 35 unique species. The classification of medicinal herbs in this system is performed using a CNN. The application has been

developed using the Android platform. The objective of this study is to examine the application of CNN techniques to distinguish various Indian leaf species. In recent times, a multitude of deep learning frameworks have been employed to detect, classify, and distinguish between different plant species. The primary objective of this research is to identify therapeutic plants that thrive in rural environments. The MobileNetV2 architecture, which is a commonly utilized CNN, was selected through the application of the transfer learning technique [18].

This paper presents a deep learning technique that utilizes a CNN built upon the VGG-16 model. CNN demonstrates high accuracy in the recognition and classification of medicinal plants. The system can learn and accurately depict intricate visual attributes found in photographs to achieve this capability. The network achieves high performance by utilizing a comprehensive dataset consisting of 25,686 photos [19]. The proposed technique effectively classifies plants across different stages of development, varying lighting conditions, and diverse image setups. This provides a reliable tool for accurately identifying plants. The research results demonstrated a significant identification rate of 98%, which indicates a strong level of proficiency in accurately classifying plants through the utilization of deep learning techniques. The proposed method offers a valuable tool for herbal medicine researchers and practitioners, as it can effectively and dependably identify herbal plants with precision. The findings of this study represent a noteworthy advancement in the application of deep learning techniques for plant identification. The suggested technique effectively addresses the challenges associated with the intricate visual characteristics of medicinal plants [20].

3. PROPOSED METHOD

This section of the study focuses on the techniques and methodologies used in the automated identification as well as classification of medicinal leaves by hybrid-aided optimizing for deep learning methodologies. This mainly involved the automatic identification of various types of medicinal leaves. For this to be accomplished, the proposed technique consists of a series of processes in preprocessing, the identification and classification technique is performed based on DeepHybrid-OptNet, is used for extraction of attributes, and hybrid optimization is utilized for enhancing the performance and optimizing the hyperparameters. Figure 1 shows the medicinal plant identification and classification process.

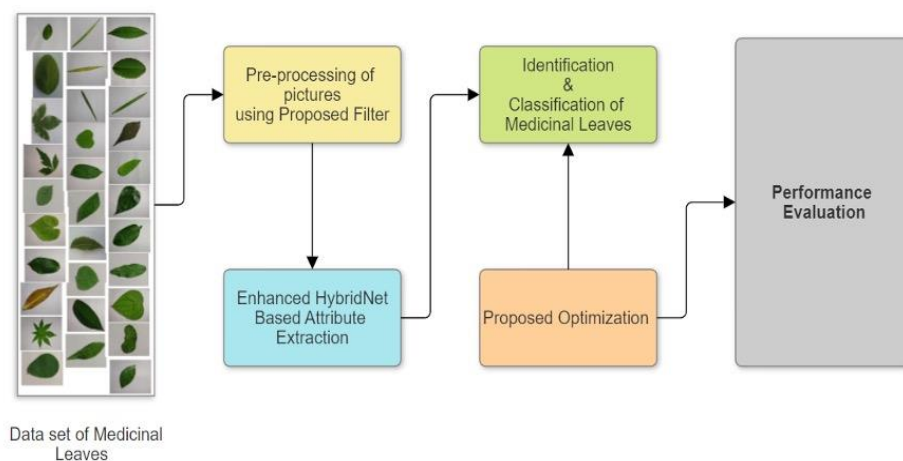


Figure 1. Medicinal plant identification and classification process

3.1. Pre-processing

The DeepHybrid-OptNet filter is utilized in the phase of pre-processing of images, where the noise or disturbance in the images is omitted. This focuses on increasing the quality of the picture by using the filter. Also, this technique conserves the signals by using the filter. This method replaces the value of the pixel with the value of the median. Therefore, reducing the disturbance in the image and increasing its resolution and quality. The value of the median is represented as $\bar{\delta}$, and the average initial value is denoted as δ in the filter that could be enhanced as given in (1).

$$d_{filter}(p, o) = \bar{\delta} + ((\alpha^2 - \beta^2)(\gamma)^{-2}) \cdot (c(p, o) - \bar{\delta}) \quad (1)$$

The advantages of the filter include that the quality of the picture that is low is enhanced as given: the signal edge is conserved better than the use of other filters because of the effects of drop-off. Finally, this technique has better performance than the traditional filters that deal with omitting disturbance in images. Additionally, it also omits the background disturbance signal as well as conserves the signal edge.

3.2. DeepHybrid-OptNet

The method proposed utilizes HybridNet technology for attribute extraction following the preprocessing of images. HybridNet consists of both a customized CNN and a customized recurrent neural network (RNN). Figure 2 illustrates the structure of the customized CNN model.

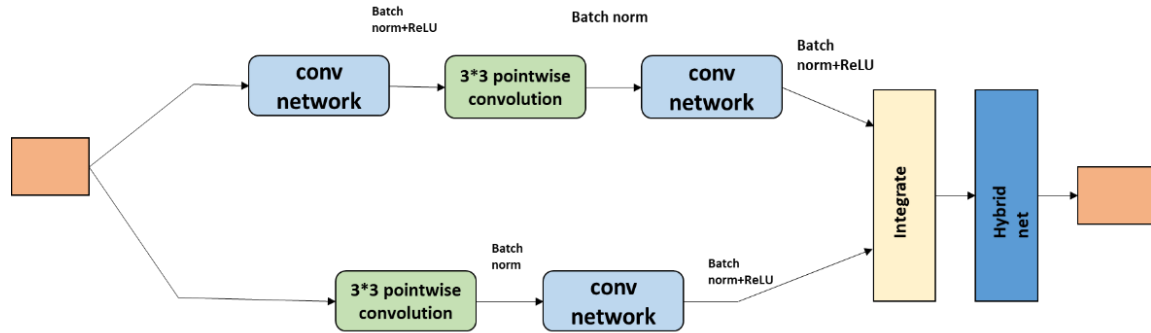


Figure 2. Customized CNN model

3.3. Feature extraction through customized CNN

The channel-wise feature extraction (CWFE) block is used specifically in this architecture considering it is flexible. The CWFE module is utilized in various ways as Version 1 and Version 2 of HybridNet. The prior inside module squeeze-and-excitation (SE), the part of the SE is placed within the HybridNet as it is layered directly followed by the last layer of convolution. Finally, the last module of CWFE has the components of SE that are to be located. Considering this computation expense, a technique is adapted for all modules of Version 1 and Version 2 of HybridNet, which has to be integrated for large components of SE. Specifically, $J \times Y$ spatial size for the complete picture is reduced to b belongs to \mathbb{T}^e by application of global mean pooling that is given (2).

$$b_e = H_{sq}(w_e) = (J \times Y)^{-1} \sum_{k=1}^J \sum_{l=1}^Y W_E(k, l) \quad (2)$$

Additionally, at the excitation phase, two small layers that are fully linked use the integrated information that is derived from the information that is squeezed. The main aim is to grasp dependency that is channel-based and further produce a series of weight modulations for every channel. The weight that is assigned to a mapping of the input feature is called recalibration of the attribute that includes the gating of blocks. This model is used along with sigmoid to gain the following as shown in (3).

$$u = H_{ex}(b, Y) = \alpha(i(b, Y)) = \alpha(Y_2 \mu(Y_1 b)) \quad (3)$$

Considering (3), the ReLU function is denoted by μ , Y_1 belongs to $\mathbb{T}_t^{e \times E}$ and Y_2 belongs to $\mathbb{T}^{E \times t}$. This represents a reduced dimensional layer along with the parameter Y_1 having reduced ratio, a max dimension layer having parameter Y_2 and ReLU. The descriptor b is used to show the channel sequence, specifically weighted. The fully linked layer as well as the less expensive channel-based scale function is utilized for rescaling the weight of the attribute map using the activation function as shown in (4). Considering the (3), $\tilde{Z} = [\tilde{z}_1, \tilde{z}_2, \dots, \tilde{z}_e]$ and also $H_{scale}(w_e, u_e)$ denotes the multiplication that is based on the channel for w_e belongs to $\mathbb{T}^{J \times Y}$ representing feature maps with scalar u_e .

$$\tilde{z}_e = H_{scale}(w_e, u_e) = u_e \cdot w_e \quad (4)$$

3.4. Customized RNN

This model is a type of customized RNN that saves the information of the latest entries by the use of feedback as it occurs in a loop. The main aim of this is to conserve the state of memory posts for an extended period due to the presence of memory cells in the model. Every cell in the model has a status of memory that is utilized for adapting the value of information before the state considering the gating elements. The status of the memory consists of gates used in controlling the information flow in the memory. The traditional Long short-term memory model has three distinct layers. The first layer is the input, followed by the recurrent layer. The equations used in the explanation of Long short-term memory are as given in (5) to (10).

$$h_v = \mu(y_h * [j_v - 1, z_v] + d_h) \quad (5)$$

$$k_v = \mu(y_k [j_v - 1, z_v] + d_k) \quad (6)$$

$$\hat{E}_v = \tanh(y_e \cdot [j_v - 1, z_v] + d_e) \quad (7)$$

$$e_v = h_v * E_{v-1} + k_v * \hat{E}_v \quad (8)$$

$$Q_v = \mu(Y_0 \cdot [j_v - 1, z_v] + d_0) \quad (9)$$

$$j_v = Q_v * \tanh(e_v) \quad (10)$$

In the set of equations, the operator * represents multiplication based on elements. Here, the forget gate is denoted as h_v , j_{v-1} shows the output of the previous segment, the weight is shown as y_h . The vector for input is represented as z_v , d_h depicts the bias, the concealed state is given as j_v , the output gate is shown as Q_v and lastly, the cell state is represented as E_v .

3.5. Hybrid optimization for performance enhancement

In the next phase, hybrid-aided optimizing is used concerning the DeepHybrid-OptNet for choosing meta-parameters, which include the rate of learning, dimensions of batch and epoch, and the activation function. Considering computation in hybrid, the smallest element for storing information is called a hybrid bit. This consists of '0' as well as '1' in a superposition that is identified from normal memory cells. This is explained as given in (11). In (11), $|\sigma|^2$ and $|\omega|^2$ represents the amplitude probability for the states '0' as well as '1' respectively. Two complex integers are denoted using σ and ω . Additionally, the condition $|\sigma|^2 + |\omega|^2 = 1$. We describe the separate optimization as given in (13).

$$|\vartheta\rangle = \sigma|0\rangle + \omega|1\rangle \quad (11)$$

$$|\varphi\rangle = \begin{bmatrix} \sigma \\ \omega \end{bmatrix} = \begin{bmatrix} \cos(\varnothing) \\ \sin(\varnothing) \end{bmatrix} \quad (12)$$

\varnothing belongs to $[0, 2\pi]$

$$Optimization_k = (\vartheta_1, \vartheta_2, \dots, \vartheta_f) = \left(\begin{matrix} \cos(\varnothing_{k1}), \cos(\varnothing_{k2}), \dots, \cos(\varnothing_{kf}) \\ \sin(\varnothing_{k1}), \sin(\varnothing_{k2}), \dots, \sin(\varnothing_{kf}) \end{matrix} \right) \quad (13)$$

In $Optimization_k$, the k^{th} path for optimization is included. \varnothing_{kl} belongs to $(0, 2\pi)$, where 1 lesser than equal to k lesser than equal to p , 1 lesser than equal to l lesser than equal to f , the various count of paths for optimization is denoted as p , and the hybrid element size is given as f . For the searching location, all hybrid paths have two positions, and all the places denote a resolution to the given challenge that is expressed as (14), (15).

$$Optimization_{ke} = \cos(\varnothing_{k1}), \cos(\varnothing_{k2}), \dots, \cos(\varnothing_{kf}) \quad (14)$$

$$Quantum Optimization_{ku} = (\sin(\varnothing_{k1}), \sin(\varnothing_{k2}), \dots, \sin(\varnothing_{kf})) \quad (15)$$

3.5.1. Initializing the matrix

The issue has dimension given as dimension and the possible paths for optimization are P separately. The path probability characterizes the hybrid bit as well as its result based on the matrix angle. At the initialization phase in hybrid, the matrix angle has to be defined as the $P * dimension$ and the angle space $(0, 2\pi)$. In (16), the lower and upper limit is represented as wd_{kl} and nd_{kl} respectively for the

l^{th} dimension, $random(0,1)$ denotes a random variable inside the range $[1,0]$. The values of given variables are constant such that $wd_{kl} = 2\pi$ and $nd_{kl} = 0$, expressed as in (17).

$$\phi_{kl} = nd_{kl} + random(0,1) \cdot (wd_{kl} - nd_{kl}), \quad (16)$$

where $1 \leq k \leq p$, $1 \leq l \leq f$

$$\phi = \begin{bmatrix} \phi_{11} & \phi_{12} & \cdots & \phi_{1f} \\ \phi_{21} & \phi_{22} & \cdots & \phi_{2f} \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{p1} & \phi_{p2} & \cdots & \phi_{pf} \end{bmatrix} \quad (17)$$

3.5.2. Elements being initialized

The hybrid optimization for a path for the matrix consists of P hybrid paths, where all the paths have two locations that select the area, and every position represents a resolution to the issue as given in (18). After the resolution space transformation, it is important to validate the value for every separate quality. In the hybrid optimization, the operator for hybrid changes the hybrid to a relative phase. The global as well as local selection is performed by changing the path as well as the angle as shown in (19).

$$Optimization \text{ or } QO = \begin{bmatrix} QO_1 \\ QO_2 \\ \vdots \\ QO_p \end{bmatrix} = \begin{bmatrix} QO_{1e} \\ QO_{1u} \\ QO_{2e} \\ QO_{2u} \\ \vdots \\ QO_{pe} \\ QO_{pu} \end{bmatrix} = \begin{bmatrix} \cos(\phi_{11}) & \cos(\phi_{12}) & \cdots & \cos(\phi_{1f}) \\ \sin(\phi_{11}) & \sin(\phi_{12}) & \cdots & \sin(\phi_{1f}) \\ \cos(\phi_{21}) & \cos(\phi_{22}) & \cdots & \cos(\phi_{2f}) \\ \sin(\phi_{21}) & \sin(\phi_{22}) & \cdots & \sin(\phi_{2f}) \\ \vdots & \vdots & \ddots & \vdots \\ \cos(\phi_{p1}) & \cos(\phi_{p2}) & \cdots & \cos(\phi_{pf}) \\ \sin(\phi_{p1}) & \sin(\phi_{p2}) & \cdots & \sin(\phi_{pf}) \end{bmatrix} \quad (18)$$

$$W(\gamma(\Delta\phi)) = \begin{bmatrix} \cos(\gamma(\Delta\phi)) & -\sin(\gamma(\Delta\phi)) \\ \sin(\gamma(\Delta\phi)) & \cos(\gamma(\Delta\phi)) \end{bmatrix} \quad (19)$$

Considering (19), the function $\gamma(\cdot)$ for angle rotation $\Delta\phi$ is expressed. The changing hybrid gate can be implemented, the updated hybrid but is given as in (20). While updating the size of the angle as well as the path direction, the algorithm for differential evolution is implemented instead of using the angle that is constant for the rotating angle in the hybrid changing gate for the proposed hybrid optimization. The process to update the angle is as given in (21). The angle for rotation is given as ϕ_{kl} ($1 \leq k \leq p$, $1 \leq l \leq f$) for *quantum paths* _{k} is updated and given as in (21).

$$\begin{bmatrix} \sigma'_k \\ \omega'_k \end{bmatrix} = W \cdot \begin{bmatrix} \sigma_k \\ \omega_k \end{bmatrix} \quad (20)$$

$$x_{kl} = \phi_{t_1 l} + H(\phi_{t_2 l} - \phi_{t_3 l}) \quad (21)$$

For (21), random integers are represented as t_1, t_2 and t_3 in range $[1, f]$. The updated angle is denoted as w_{kl} and the previous angle is given as ϕ_{kl} have particular probability and is crossed, the function for crossing is expressed as given in (22). The probability of crossing over is represented as ERo that is produced randomly within the range $[0,1]$. A random variable inside range $[1, f]$ is given as $random_k$. The angle of rotation has a magnitude that is given by $|w_{kl} - \phi_{kl}|$. Here we have the angle of rotation $\gamma(\Delta\phi) = U(\sigma_k, \omega_k) \times |w_{kl} - \phi_{kl}|$. The rotating direction of the angle is given as U which gives us the enhanced equation as given in (23). The value for evaluation of the quality status for all paths is described. It is important to transform the resolution space of the separate location. We assume that the resolution space is explained as given in (24). The proposed method attains an increased efficiency using a classifier. It describes a positive variable to depict the higher output for the resolution. The decrease in classifier rate error for fitness (fit) is given in (26).

$$w_{kl} = \begin{cases} x_{kl}, & \text{random lesser than or equal to } ERO = \text{random}_k \\ \phi_{kl} & \text{else} \end{cases} \quad (22)$$

$$U(\sigma_k, \omega_k) = \text{sign of } (\sigma_k \times \omega_k) \quad (23)$$

$$T_{ke} = (c(1 - \sigma_k) + d(1 - \sigma_k))(2)^{-1} \quad (24)$$

$$T_{ku} = (c(1 - \omega_k) + d(1 - \omega_k))(2)^{-1} \quad (25)$$

$$\text{fit}(z_k) = \frac{\text{Error rate of classifier}(z_k) = \text{count of misidentified instances}}{\text{Total count of instances}} * 100 \quad (26)$$

4. PERFORMANCE EVALUATION

This section presents the performance outcomes of the proposed deep HybridNet model applied to medicinal plant leaf images. It includes a comparative analysis against state-of-the-art classification techniques. The results highlight the superior classification accuracy and efficacy of the deep HybridNet model in accurately categorizing medicinal plant leaf images compared to existing techniques.

4.1. Dataset details

This research utilizes two types of datasets for performance evaluation. The folio dataset [21] comprises 32 plant species' leaf images captured under optimal daylight conditions with white backgrounds at the University of Mauritius and nearby areas. Meanwhile, the Mendeley Medicinal Leaf dataset [22] used in this study features images from 30 medicinal plants, totaling 1,835 leaf images. Acknowledging the impact of dataset size, class distribution, and data quality on system performance, data preprocessing techniques were applied to ensure dataset cleanliness and consistency. Notably, Figure 3 showcases the folio dataset, while Figure 4 displays samples from the Mendeley Medicinal Leaf dataset.

4.2. Folio dataset

The folio dataset [21] is a standard leaf dataset used in plant recognition. The leaves were placed on a white background and then photographed. The pictures were taken in broad daylight to ensure optimum light intensity. It contains 32 different species taken from plants on the farm of the University of Mauritius and nearby locations. Figure 3 shows a sample dataset of folio.

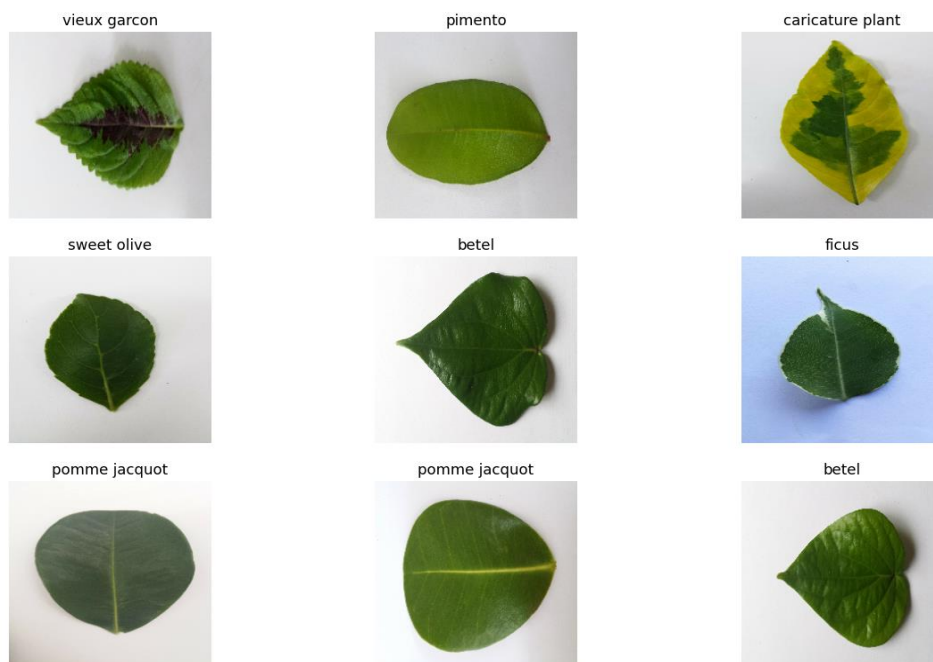


Figure 3. Sample dataset of folio

4.3. Mendeley leaf dataset

We used the benchmark dataset of medicinal plant leaf classification, i.e., Mendeley Medicinal Leaf [22]. The dataset, representing images from 30 different medicinal plants, was selected for this study. The selected dataset contained a total of 1,835 leaf images. A system's performance is affected by factors like the dataset size, class distribution, and data quality. To address this concern, data preprocessing was employed to clean the dataset. Figure 4 depicts some of the leaf samples of the Mendeley Medicinal Leaf dataset.

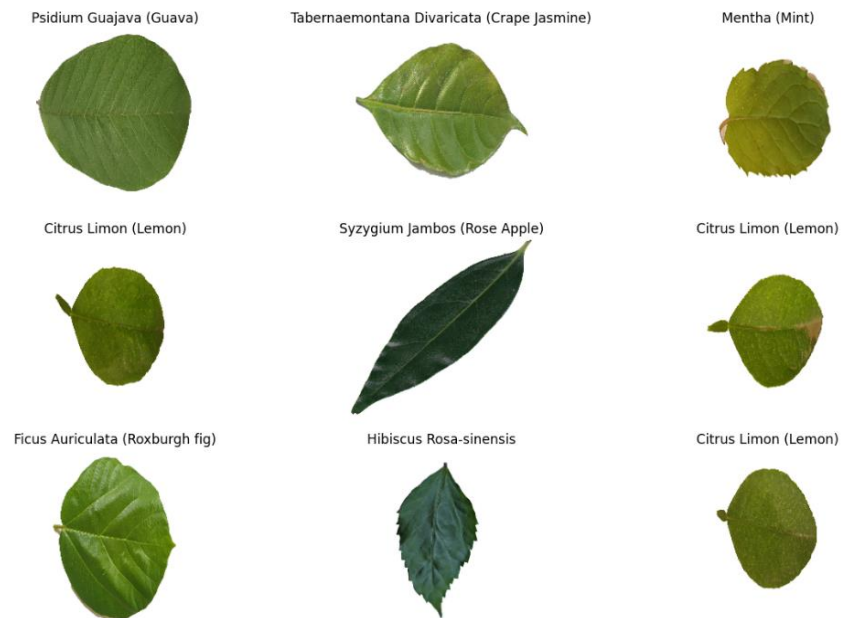


Figure 4. Sample image of the medicinal dataset

4.4. Evaluation metrics

Evaluation metrics play a vital role in optimizing classifiers for the accurate detection and classification of medicinal plant images. In this study, we evaluated the trained models based on commonly used performance metrics in this domain, which include accuracy, sensitivity (recall), precision, and the F1-score. Accuracy measures the proximity between predicted and target values, while sensitivity focuses on the ratio of correctly identified positive instances. True negatives (TNs) and true positives (TPs) represent correctly classified negative and positive instances, respectively, contributing to successful classification and detection. False negatives (FNs) and false positives (FPs) denote misclassifications. These metrics guide the fine-tuning of classifiers to achieve optimal performance in medicinal plant image classification. The formulae for the calculation of the metrics used in this study. DeepHybrid-OptNet is evaluated by comparing with standardized orthopedic assessment tool (SOAT) [23]–[26] models on the folio dataset and on the Mendley dataset [27].

4.5. Performance metrics

The evaluation of classifiers involves several key performance metrics: accuracy, recall (or sensitivity), precision, and the F1-score. Accuracy measures the ratio of correctly predicted instances among the total evaluated. Recall quantifies the ratio of accurately predicted positive values within the actual positive instances, while precision assesses the accuracy of positive predictions within the predicted positive class. The F1-score provides a balanced assessment of the classifier's performance by considering both recall and precision through their harmonic mean. Examination of classification reports and confusion matrices enabled a comprehensive evaluation of classifier performance across various feature sets, facilitating a comparative analysis of their effectiveness. This systematic approach allowed for a thorough understanding of how different classifiers performed in diverse scenarios based on these crucial metrics.

4.6. Results

The classification results for various medicinal leaves show a remarkably high level of accuracy. Most plant species, including Ashanti blood, Barbados cherry, and chrysanthemum, have achieved perfect

scores across precision, recall, and F1-score metrics in Table 1. This indicates that the model is exceptionally effective in correctly identifying these species, with no false positives or negatives. However, there are notable exceptions. For instance, the classification of 'guava' shows a slightly lower precision, suggesting some misclassification, and 'pimento' exhibits a lower recall, indicating missed instances of this species. Despite these minor deviations, the overall performance of the model is impressive, suggesting its high reliability for applications in botany, pharmacology, or herbal medicine, where accurate identification of plant species is critical. The few areas where the model underperforms could potentially be improved with further tuning or by using a more varied training dataset. Figure 5 shows the performance analysis on the folio dataset.

Table 1. Metrics on the folio dataset

Classes	Precision	Recall	F1-Score
Ashanti blood	1	1	1
Barbados cherry	1	1	1
beaumier du perou	1	1	1
Betel	1	1	1
Bitter orange	1	1	1
Caricature plant	1	1	1
Chinese guava	1	1	1
Chocolate tree	1	1	1
Chrysanthemum	1	1	1
Coeur demoiselle	1	1	1
Coffee	1	1	1
Croton	1	1	1
Duranta gold	1	1	1
Eggplant	1	1	1
Ficus	1	1	1
Fruitier	1	1	1
Geranium	1	1	1
Guava	0.83	1	0.91
Hibiscus	1	1	1
Jackfruit	1	1	1
Ketembilla	1	1	1
Lychee	1	1	1
Mulberry leaf	1	1	1
Papaya	1	1	1
Pimento	1	0.8	1
Pomme jacquot	1	1	1
Rose	1	1	1
Star apple	1	1	1
Sweet olive	1	1	1
Sweet potato	1	1	1
Thevetia	1	1	1
Vieux garcon	1	1	1

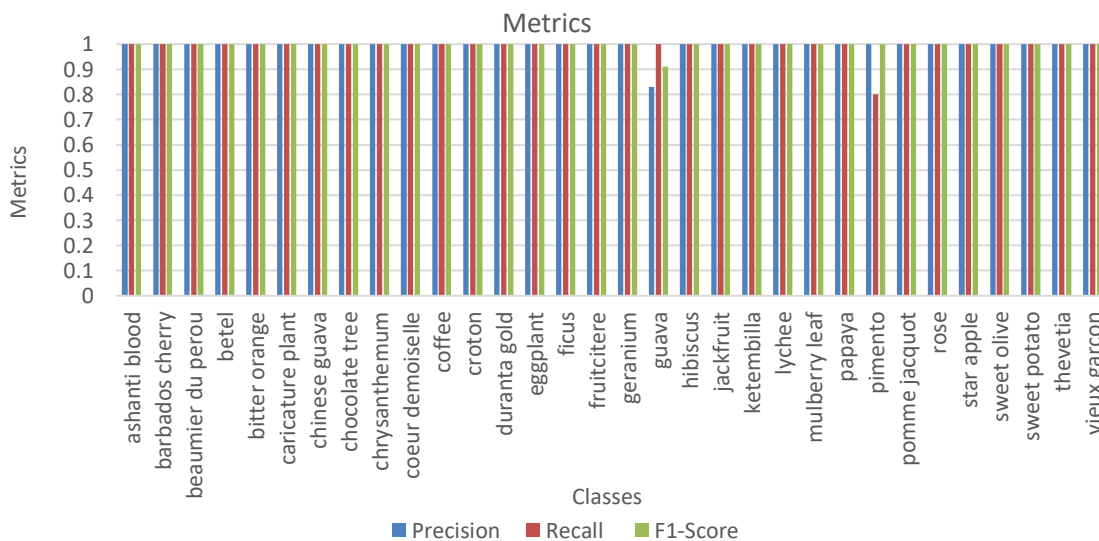


Figure 5. Performance on folio dataset

4.7. Metrics comparison on folio dataset

Figure 6 compares the accuracy of various machine learning models, showing a clear trend where more complex or composite models outperform simpler ones. K-nearest neighbor (KNN) has the lowest accuracy, which might be due to its sensitivity to noisy data, followed by the decision tree, which can suffer from overfitting. The CNN+LR (logistic regression) model shows improved performance, suggesting benefits from combining deep learning with traditional regression techniques. Standalone CNN exhibits a similar level of accuracy, indicating that for this task, logistic regression may not add significant value to CNN's performance. Ensemble strategies, possibly represented by ES, show high accuracy, underscoring the effectiveness of combining predictions from different models. HybridNet stands out with the highest accuracy, nearly perfect, which suggests it effectively leverages multiple model architectures to achieve superior generalization. This chart indicates that for complex tasks, hybrid and ensemble methods are likely more effective, utilizing the strengths of various algorithms to enhance predictive performance.

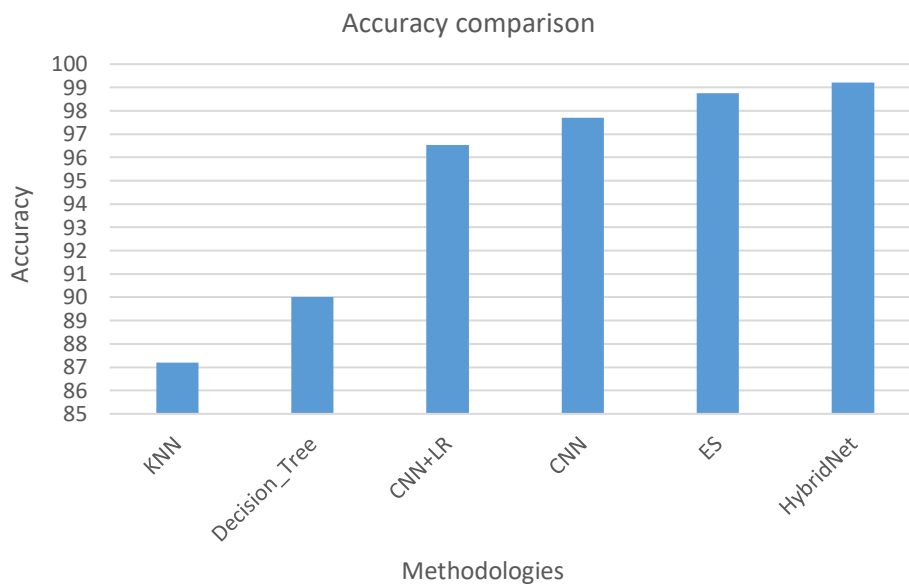


Figure 6. Accuracy comparison on folio dataset

Table 2 outlines the precision, recall, and F1-score for a classification task involving 30 different classes of medicinal leaves on the Mendeleev leaf dataset. The majority of the classes achieve perfect scores of 1 across all three metrics, indicating a model that is highly precise and consistent in identifying these classes without misclassification or omission. However, there are some deviations from perfection. For instance, class 3 exhibits a recall of 0.92 but maintains perfect precision, suggesting that while all the predictions made for this class are correct, the model fails to identify 8% of actual instances. Similarly, classes 8 and 9 have perfect precision and recall but have an F1-score of 0.94, indicating some imbalance between precision and recall. Class 10 has an F1-score of 1 despite a recall of 0.89, which usually suggests a compensatory high precision, although precision is also 1 here, which could indicate an error in the reporting or a rounding inconsistency. Class 14 shows perfect precision and an F1-score of 1 but a slightly lower recall of 0.93, indicating some instances of this class were missed by the model. Classes 16 and 17 have perfect precision but their F1-scores of 0.96 reflect a slight deficiency in recall. Class 18 shows a precision of 0.92, which means there were some false positives, yet the F1-score is perfect, which typically would not be possible unless the recall is also perfect, indicating a potential discrepancy in the data. Class 19 has a slightly lower F1-score of 0.89, suggesting either a recall or precision issue. Lastly, class 20 has the lowest precision at 0.8, indicating that 20% of the instances classified as this class was incorrect, yet it shows a perfect F1 score, which again might suggest data reporting inconsistencies. Overall, the data implies a highly effective classification model with specific areas for improvement. The inconsistencies in the F1 scores for certain classes could be due to rounding or calculation errors, as F1 scores are the harmonic mean of precision and recall and typically would not be perfect if either of those metrics is less than 1. The model's performance on this task is exemplary, with room for minor enhancements in certain classes. Figure 7 shows the evaluation of the metric.

Table 2. Medicinal leaf dataset

Class	Precision	Recall	F1-score
1	1	1	1
2	1	1	1
3	1	0.92	0.96
4	1	1	1
5	1	1	1
6	1	1	1
7	1	1	1
8	1	1	0.94
9	1	1	0.94
10	1	0.89	1
11	1	1	1
12	1	1	1
13	1	1	1
14	1	0.93	1
15	1	1	1
16	1	1	0.96
17	1	1	0.96
18	0.92	1	1
19	1	1	0.89
20	0.8	1	1
21	1	1	1
22	1	1	1
23	1	1	1
24	1	1	1
25	1	1	1
26	1	1	1
27	1	1	1
28	1	1	1
29	1	1	1
30	1	1	1

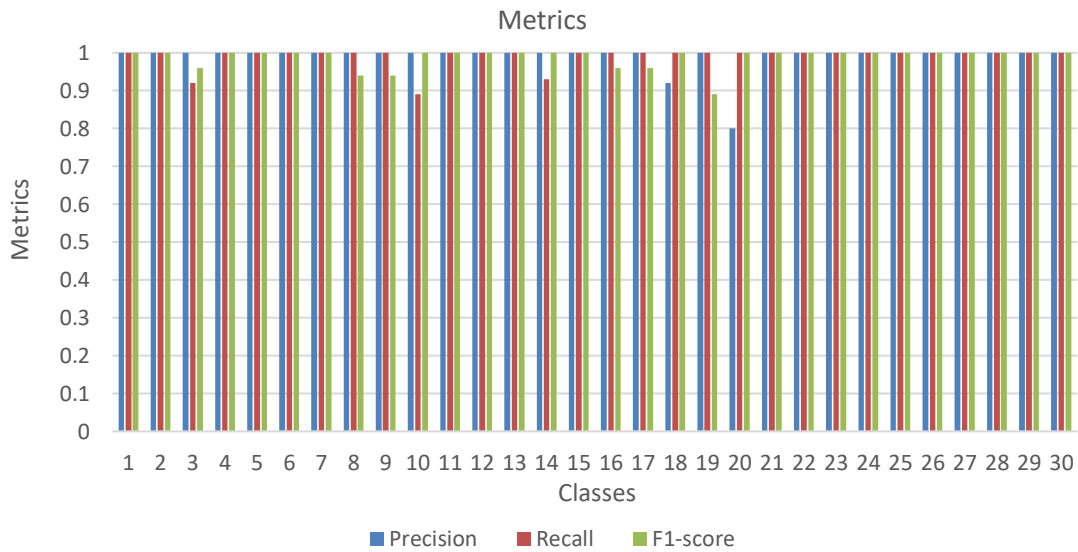


Figure 7. Metrics

Figure 8 illustrates a performance comparison among four deep learning models, VGG16, VGG19, DenseNet201, and HybridNet, using the Mendley leaf dataset across four metrics: precision, recall, F1-score, and accuracy. HybridNet emerges as the superior model, outshining the others on all fronts with its performance metrics surpassing the 98% threshold. DenseNet201 ranks as close second, exhibiting robust performance, though not at HybridNet's level. VGG19, while outperforming VGG16, falls behind DenseNet201, indicating a moderate capability. VGG16 is the least effective according to the graph, with the lowest precision, recall, and F1-score, but its accuracy is on par with VGG19. Overall, HybridNet's dominance across all metrics suggests it is the most reliable and accurate model for classifying leaves in the Mendley dataset, showcasing its efficacy in yielding precise and consistent classifications.

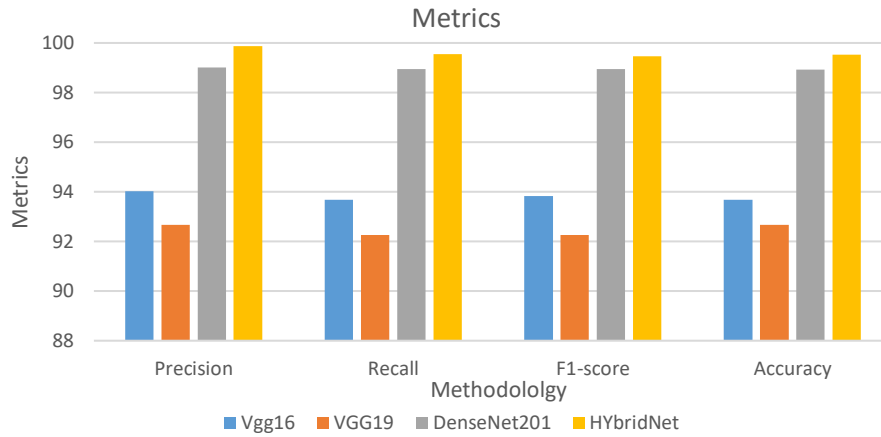


Figure 8. Metrics comparison

The receiver operating characteristic (ROC) curve in the image Figure 9 provides a graphical representation of a classification model's diagnostic ability. Each line represents the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) for a different class (in this case, various plants or substances) when using a continuous classifier output like probabilities. The listed area under the curve (AUC) values for each class are exceptionally high, with most of them at 1.00, which indicates a perfect classification with no overlap between the positive and negative distributions. A couple of classes have AUC values slightly less than 1.00, such as *Artocarpus Heterophyllus* (Jackfruit) and *Tabernaemontana divaricata* (Crape jasmine), which still indicates excellent classification performance but with a minimal level of misclassification when compared to the others. The architecture's effectiveness is evident from the near-perfect AUC values, which suggest that HybridNet is highly adept at distinguishing between the different classes with a high degree of accuracy, minimizing both false positives and false negatives.

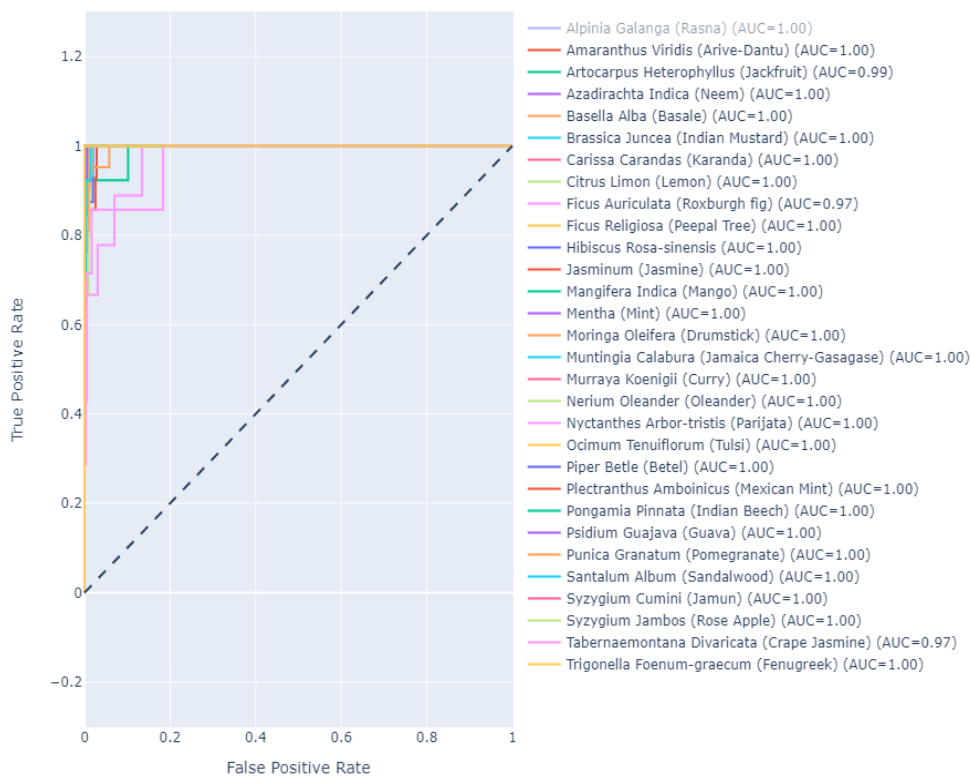


Figure 9. ROC curve on the medicinal dataset

5. CONCLUSION

This research proposes DeepHybrid-OptNet for the identification and classification of medicinal plants; this architecture comprises customized CNN and RNN integrated to extract the efficient feature along with a hybrid optimization module developed for enhancing the performance by selecting the optimal parameters for training and evaluating the module. The proposed DeepHybrid-OptNet model has been rigorously evaluated using two datasets: the Folio dataset and the Mendeley Medicinal Leaf dataset; The evaluation metrics, accuracy, recall (sensitivity), precision, and F1-score, were employed to measure the model's performance. The deep HybridNet model has demonstrated exceptional accuracy and reliability in classifying medicinal plant leaves, which holds significant implications for applications in botany, pharmacology, and herbal medicine. The few instances of suboptimal performance suggest opportunities for further enhancement, potentially through model refinement or expanded training datasets. Overall, the study underscores the effectiveness of the deep HybridNet model and its potential as a tool for accurate plant species identification.

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