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RESEARCH ARTICLE

DEEP LEARNING-BASED CLASSIFICATION OF LICHENS IN WESTERN GHATS USING AERIAL IMAGES

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Abstract – Lichens are interesting composite organisms that evolved and diversified after a symbiotic association between algae and fungi and lichens are estimated to cover roughly 10% of terrestrial ecosystems. The limited number of images in datasets makes it difficult to classify the lichen classes and the dependability rate of the existing study is still quite low. In this paper, a novel deep-learning model is proposed for the classification of lichens using aerial images. The input aerial images are gathered from western ghats and the collected images are pre-processed utilizing a Contract stretching adaptive histogram equalization (CSAHE) filter to increase the image quality. The Mask RCNN model is implemented to extract the relevant features from the images and also segment the region of the enhanced images. The Deep neural network is used for classifying the lichens from the western ghats. According to the result, the proposed model attains a 99.12% success rate for the classification of lichens. The proposed Mask RCNN enhances overall accuracy of 2.53%, 6.39%, and 1.88%, better than RNN, CNN, and RCNN. The proposed DNN improves its reliability by 8.13%, 4.45%, and 0.87% better than FNN, GNN, and DBN respectively. The proposed model enhances the overall accuracy of 38.33%, 10.12%, and 4.12% better than DCNN, CNN, and XGBOOST.

Keywords *– Deep neural network, Lichens, Contract stretching adaptive histogram equalization, Mask RCNN.*

1. INTRODUCTION

Lichens are interesting composite organisms that evolved and diversified after a symbiotic association between algae and fungi and lichens are estimated to cover roughly 10% of terrestrial ecosystems. In the biologically rich Western Ghats of India, lichens—symbiotic organisms made up of fungi and photosynthetic partners like algae or cyanobacteria—play a critical role [1-2]. The Western Ghats are home to the greatest percentage of lichens in India—nearly 45%—of any other location. Of these, the Western Ghats are home to 253 indigenous species. Tamil Nadu contains more lichens than any other state, with 657 species. Karnataka, Kerala, and Maharashtra are next with 336, 288, and 91 species. Classifying lichens in this region using deep learning (DL) methods presents a compelling area of research due to the limitations posed by the sheer diversity and ecological significance of lichens in this unique ecosystem [3-5]. The Western Ghats are recognized as a global biodiversity hotspot, hosting a diverse array of lichen species that thrive in varied ecological niches spanning elevations and climatic zones. Traditionally, lichen classification relies heavily on morphological and chemical traits, a labor-intensive process that can be limited by subjectivity and expertise. Leveraging DL, a branch of artificial intelligence (AI) that excels in recognizing patterns within complex data, offers a promising avenue to augment traditional taxonomy with automated image-based identification [6-8].

Deep learning models are trained using large datasets of lichen images, capturing intricate visual features that are often challenging for human observers to discern. By employing convolutional neural networks (CNN) architecture for image recognition tasks, researchers develop systems capable of distinguishing between subtle variations in lichen morphology and coloration [9-11]. This approach has the potential to accelerate the identification process and enhance our understanding of lichen diversity in the Western Ghats. However, applying deep learning to lichen classification in the Western Ghats encounters several notable limitations. Firstly, gathering a comprehensive and representative dataset of lichen images from this region is a significant challenge. Lichen diversity is vast and distributed across varied habitats, necessitating extensive fieldwork to collect high-quality images encompassing different species and environmental conditions. Limited availability of such data can impede the development and generalization of DL models [12-14].

Another significant challenge is the adaptation of DL models to handle intra- and interspecies variability in lichen morphology. Lichens exhibit considerable phenotypic plasticity influenced by environmental factors, making it challenging to develop robust classifiers that can accurately generalize across diverse conditions. Overcoming these hurdles could pave the way for a more effective and comprehensive understanding of lichen diversity and ecological dynamics in this ecologically vital region. In this paper, a novel DL model is developed for the classification of lichens in western ghats. The suggested work's main contributions are as follows.

- In this paper, a DL model is recommended for the categorization of lichens using aerial images.
- The input aerial images are gathered from western ghats and the collected images are pre-processed utilizing a CSAHE filter to enhance the image.
- The Mask RCNN model is implemented to extract the relevant features from the images and also segment the region of the enhanced images.
- The Deep neural network is used for classifying the lichens from the western ghats.

The remaining sections of this paper are planned as follows. Chapter 2 offers an outline of the literature, followed by a full explanation of the proposed model for lichen detection in Chapter 3, results and discussion in Chapter 4, and a conclusion detailed in Chapter 5.

2. LITERATURE SURVEY

Researchers have offered numerous studies in recent years for lichen classification techniques. This section is a succinct summary of some of the recent work.

In 2021 Galanty, A et al., [15] offered a tool based on a deep convolutional neural network (DCNN) that may help identify different species of Cladonia lichen. This CNN has advanced to a classification level that is frequently comparable to that of humans. Although the trained model's accuracy of 60.94% is acceptable, further reliability testing is still needed for automated lichen species recognition.

In 2021 Galanty, A et al., [16] created DCNN to identify the species of lichen. The test is helpful for the first in-field identification of Cladonia species and achieves 69.93% accuracy for lichen species detection. When compared to other models, the test result of the developed model is insufficient.

In 2022 Presta, A et al., [17] employed a machine-learning approach based on patch classification to classify lichen taxa from pictures. Using CNN as feature extractors, the lichen was classified. With a particularly constructed descriptor, 89% of the dependability rate is measured utilizing the lichen dataset.

In 2023 Sandino, J et al., [18] created a DL model that will allow for accurate vegetation mapping and surveillance in ASPAs. The drones gather supervised ML classifiers, and ground control points (GCPs). Extreme gradient boosting (XGBoost) was used to train the model, and mapping of moss and the effective recognition and lichens was accomplished with an average recognition rate of 95%.

In 2023 Richardson, G. et al., [19] created ML algorithms in Québec and Labrador, Canada, to forecast the percentage of lichen covered in Sentinel-2 data. With a 5.2% mean absolute error, dense neural network (DNN) surpassed the other one with an accuracy of 0.76. Employing a Sentinel-2 image mosaic and a trained DNN, a regional lichen map was produced.

According to the survey, the existing studies on automated lichen classification using deep learning methods highlight several limitations. One common limitation observed across the existing surveys is the reliance on relatively small and potentially biased datasets for model training and evaluation. The reliability rate of the existing study remains very low when compared with other models. To overcome these issues a novel DL model is developed for the classification of lichens.

3. PROPOSED METHOD

In this section, a novel DL framework is developed for the classification of lichens using aerial images.

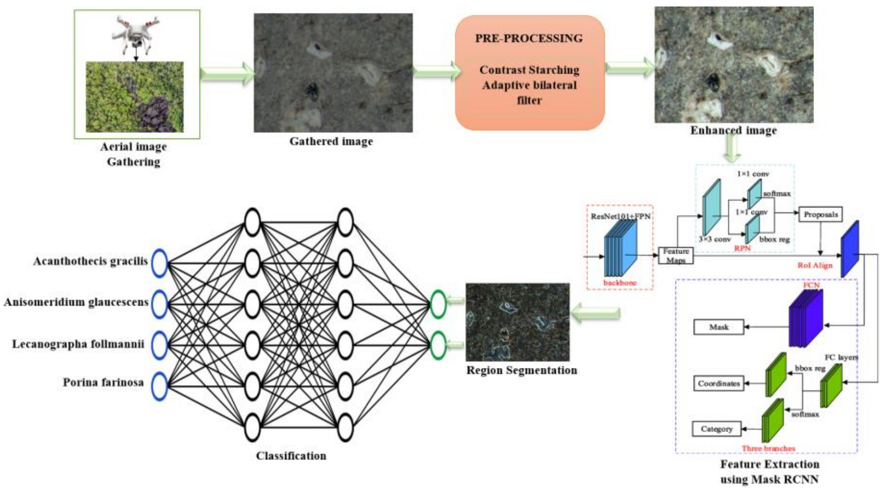

Figure 1. Block Diagram of suggested framework

The input aerial images are gathered from western ghats and the collected images are pre-processed utilizing CSAHE filter to enhance the image. The Mask RCNN model is implemented to extract the relevant features from the images and also segment the region of the enhanced images. The Deep neural network is used for classifying the lichens from the western ghats.

3.1. Data pre-processing

To improve the quality of the collected photos, pre-processing is done using the CSAHE approach. The output pixel values from the input images are produced by linear filters that are created by combining the pixel ideals of neighboring inputs. By applying CSAHE to images, the technique aims to enhance contrast between different structures, improve image visualization, and potentially help in the detection and diagnosis of lung cancer. Using a programmable transfer function created from the properties of the input photos, the new level is applied to each pixel. For this discussion.

$$\mathfrak{r}_{g} = |k_{max-}k_{min}| \quad (1)$$

Where k_{max-} and k_{min} denotes the input images with the highest and lowest intensity values, respectively. An additional intensity value is applied to each pixel, as defined in Equation (2).

$$\mathcal{P}_{\mathfrak{r}}=\begin{cases} k_{i}-u_{i} & ,if\ k_{i}=\mathcal{L}_{max} \\ k_{i}+u_{i} & ,if\ k_{i}=\mathcal{L}_{min} \end{cases} \quad (2)$$

$$N_{j} = k + \mathfrak{r}_{j}\left|\frac{x_{n}-x_{min}}{x_{max}-x_{min}}\right| \quad (3)$$

To change the value of each pixel, utilize the formulas that were previously explained. Image noise is reduced and features are improved in this way. The final output image is obtained by combining all the sub-images generated through this process, enhancing the overall visual quality and details.

3.2. Feature Extraction

The process of converting raw pixel data into a set of representative features that draw attention to important patterns or characteristics in an image is known as feature extraction. In many computer vision applications, such as object identification, picture retrieval, and image categorization, it is a crucial stage toward enabling machines to read and understand visual content. In this phase, the Mask CNN Algorithm is used to extract the necessary features from the segmented image. Faster RCNN is an extension of Mask RCNN, a system for instance segmentation. It is broken down into two phases: the first generates ideas by scanning the image, and the second generates masks and bounding boxes by categorizing those ideas.

Target identification and object segmentation at the pixel level can be done concurrently by the instance segmentation algorithm model known as Mask RCNN. To extract features and obtain the relevant feature maps, the image must be analyzed employing the earlier trained Mask RCNN model. The SoftMax classifier is then used to binary classify the foreground and background. Frame regression yields more precise information about possible frame positions. Moreover, non-maximum suppression excludes a portion of the ROI. Next, a fixed-size feature map can be created by transferring each ROI's feature map and final ROI to the RoIAlign layer. The flow eventually splits into two divisions: the path that enters the fully convolutional network (FCN) for pixel segmentation and the FCN for object detection and frame regression.

3.3. Deep Neural Network

DNN is a neural network with several layers of connected nodes. Three phases of layers are commonly seen in DNNs: input, hidden, and output layers. The initial input data, such as a word or image, is received by the input layer. Relevant features or representations are extracted from the input data by the intermediate layers. Because deep networks have multiple hidden layers, they can learn hierarchical models for the input data, which are then used by the output layer to produce the final estimate or categorization.

$$k = \begin{cases} n < 0 & f(n) = 0 \\ n \geq 0 & f(n) = j \end{cases} \quad (4)$$

Rectified Linear Unit (ReLU), a nonlinear activation function is widely used in regression analysis. The ReLU yields zero if the parameter value (z) is less than zero; if it is greater than zero, it yields the input value indicated in equation (4). Currently, the DNN model is used to classify lichens with a higher level of dependability than other cutting-edge networks.

4. RESULTS AND DISCUSSION

In this research, the lichen dataset [] is utilized for the classification of lichen in western ghats. Lichens are more complex organisms than fungi. They arise from the combination of one or more fungal and algal races. 2,300 species of lichens, representing 305 taxa and 74 families, have been gathered from various parts of India, a country known for its immense diversity worldwide.

From figure.2, the input images (column 1) are pre-processed (column 2) utilizing a CSAHE filter to enhance the image. The generated images are feature extracted (column 3) and the regions are segmented (column 4) by implementing the Mask RCNN model. Finally, the DNN model is used for the classification of Lichen classes (column 5).

4.1. Performance Analysis

The efficacy of the suggested approach was suggested for identifying lichen classes using precise indices including accuracy, recall, and F1 score.

$$Specificity = \frac{N_{gTr}}{N_{gTr}+P_{F}} \quad (5)$$

$$Accuracy = \frac{P_{Tr}+N_{gTr}}{Total\ no\ of\ Sample} \quad (6)$$

$$Precision = \frac{P_{Tr}}{P_{Tr}+P_{F}} \quad (7)$$

$$Recall = \frac{P_{Tr}}{P_{Tr}+N_{gF}} \quad (8)$$

$$F1\ Score = 2\left(\frac{Pre*Recall}{Pre+Recall}\right) \quad (9)$$

Figure 4 describes the lichens detection of the proposed model and other existing techniques in the form of F1 Score, recall, accuracy, and precision.

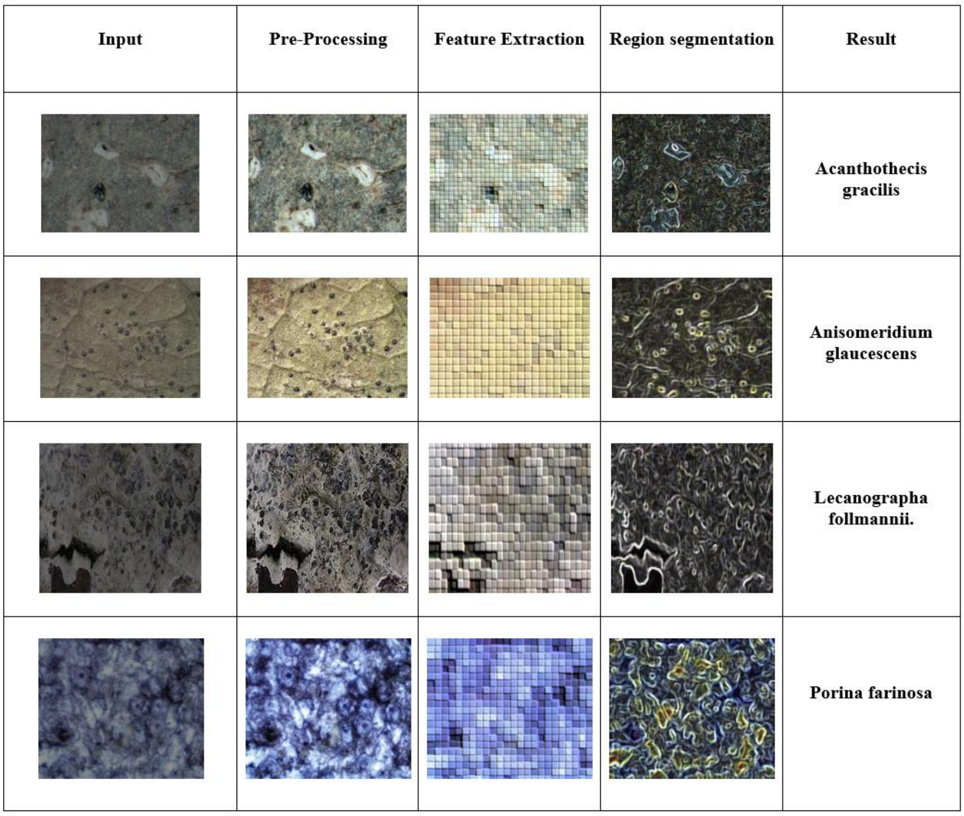

Figure 2. Experimental result of the suggested approach

Table 1. Experimental Evaluation of the Proposed Model

Classes	Accuracy	Precision	Recall	F1-Score
Acanthothecis gracilis	99.34	96.88	95.32	97.85
Anisomeridium glaucescens	99.33	98.05	94.55	97.03
Lecanographa follmannii	98.88	96.34	96.17	98.23
Porina farinosa	98.96	97.01	98.28	98.22

The efficacy of the suggested approach to classify lichens is illustrated in Table 1. The suggested approach achieves a 99.12% success rate. The proposed model receives an F1 score of 97.83%.

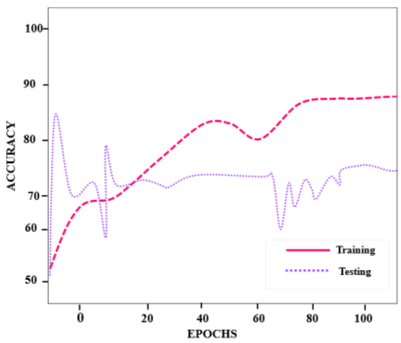

Figure 3. Accuracy curve of the suggested approach

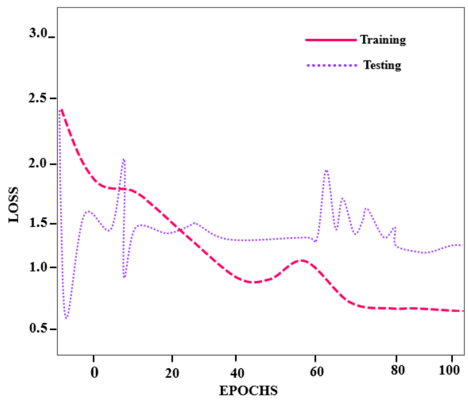

Figure 4. The loss curve of the recommended approach

The accuracy curve in Figure 3 demonstrates that accuracy rises as epochs rise. The approach's loss diminishes as the number of epochs, illustrated by the epoch compared to the loss curve in Figure 4

4.2. Comparative Analysis

The efficacy of the neural network design was measured and the findings obtained superior accuracy. The proposed model with four neural network classifiers such as RNN, CNN, and RCNN was evaluated for competency.

Table 2. Comparison of different networks with suggetsed model

Techniques	Precision	Specificity	Recall	F1 score	Accuracy
RNN	95.31	94.84	94.29	88.87	96.59
CNN	92.57	92.19	92.51	92.32	92.73
RCNN	94.19	93.48	95.48	94.89	97.24
Proposed Mask RCNN	97.88	96.60	97.39	98.44	99.12

According to Table 2. the suggested Mask RCNN improves overall accuracy by 2.53%, 6.39%, and 1.88%, better than RNN, CNN, and RCNN. Proposed Mask RCNN maintains a 99.12% high accuracy range.

Table 3. Comparison of existing approach with proposed DNN

Methods	Accuracy	Specificity	F1-score	Precision	Sensitivity
FNN	90.99	92.14	93.31	87.99	92.33
GNN	94.97	88.19	87.27	88.74	90.55
DBN	98.25	90.71	92.18	93.22	82.58
Proposed DNN	99.12	98.84	95.97	98.76	96.98

While identifying the network with the most accurate classification, Table 3 compares several standard DL networks. When contrasted to the proposed model the traditional DL systems failed to yield enhanced fallouts. The proposed DNN improves its reliability by 8.13%, 4.45%, and 0.87% better than FNN, GNN, and DBN respectively.

Table 4. Contrast of suggested approach with the previous frameworks

Author	Technique	Accuracy
Galanty, A et al., [15]	DCNN	60.79%
Presta, A et al., [17]	CNN	89%
Sandino, J et al., [18]	XGBOOST	95%
Proposed Model	DNN	99.12%

Based on Table 4, the suggested model improves the overall accuracy by 38.33%, 10.12%, and 4.12% better than DCNN, CNN, and XGBOOST, respectively**.** According to the comparison above, the developed model surpasses previous frameworks regarding reliability. However, in contrast to the suggested framework, the previous model does not perform well. Therefore, the recommended approach estimated findings are quite trustworthy for lichen classification.

5. CONCLUSION

In this research, a novel DL approach is developed for the categorization of lichens using aerial images. The input aerial images are gathered from western ghats and the collected images are pre-processed utilizing CSAHE filter to enhance the image. The Mask RCNN model is implemented to extract the relevant features from the images and also segment the region of the enhanced images. The Deep neural network is used for classifying the lichens from the western ghats. According to the result, the proposed model attains 99.12% of success rate for classification of lichens. The proposed Mask RCNN enhances overall accuracy of 2.53%, 6.39%, and 1.88%, better than RNN, CNN, and RCNN. The proposed DNN improves its reliability by 8.13%, 4.45%, and 0.87% better than FNN, GNN, and DBN respectively. The proposed model enhances the overall accuracy of 38.33%, 10.12%, and 4.12% better than DCNN, CNN, and XGBOOST. In the future, the proposed framework will be enhanced with an enhanced model for the categorization of lichens.

CONFLICTS OF INTEREST

This paper has no conflict of interest for publishing.

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