Research Article

Lichen Element Based Autonomous Air Pollution Monitoring Around Smart Cities – A Deep Learning Approach

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Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 28 April 2021

Abstract: — Increasing population across the globe affects the environment through the excessive usage of available natural resources and affects the quality of air to a greater extent. Air pollution has become most vulnerable for the existence of the living organisms. Smart cities projects concentrate on implementing the core technological infrastructure there by ensuring the quality of life to their citizens. Reducing the air pollution remains a main objective while implementing the smart city projects. Lichen elements are the natural bio indicators that are can be used as a natural indicator of climatic change and air pollution effects. In this proposed work lichen elements are located on the surface of the buildings across the smart cities. Advancements in hardware and computational software widens the usage of deep learning approaches for image classification. The proposed RESNET model is capable of receiving the input and extracting the color features out of the lichen images. The Unmanned Ariel Vehicle is an autonomous source for collecting the lichen images located on the surface of the buildings. The extracted features pass through the stack of convolution and max pool layers in RESNET architecture. Finally, the input image is flattened and classified based on the pollution level. The accuracy of the proposed architecture is validated with the traditional methods support vector machine and VGG-16 deep learning approach. The advanced computational techniques prove that the lichen images can be effectively used for air pollution monitoring around the smart cities.

Keywords: Air Pollution, Smart city, Lichen, RESNET, Unmanned Ariel Vehicle, Support Vector machine

1. Introduction

The living organisms in our world need protection from various particles like x-rays, UV rays, Cosmic rays that blitz around the planet and this protection is provided by Earth's atmosphere. For the favor of our life sustainability, Earth's atmosphere also helps us to maintain the normal temperature by balancing it around the planet. The unseen gaseous liquids covering the planet with the highest proportion of oxygen and nitrogen elements are air [1]. The main purpose of air is the passing the sound waves from source to destination which enables the people to hear sound. An air accumulation is the body of the air that is responsible for the temperature to be maintained were it exists.

One of the major threats the world facing now is environmental pollution which creates serious issues to our society and scientists are involved in identifying and analyzing these pollution levels that affect the living organisms [2-5]. There are many forms of environmental pollution. The air pollution mainly led by the mixing of toxic substances with the air that disturbs the living organisms. The other reasons for air pollution include the gas emitted from vehicles and factories, burning of plastic materials which is the main reason for acid rains, which in turn increasing the global warming – a major threat to human race.

According to an estimated survey, the air pollution slays seven million people every year. As per the data from World Health Organization (WHO), 9 out of 10 people breathe air containing high levels of pollutants. WHO is working along with countries to improve the quality of the air and to monitor the pollution. Air pollution pose a major threat to the health of living organisms and climate which can be in any form that includes the smog over the cities, smoke inside the home. Due to the collective effect of outdoor and indoor air pollution, approximately there are seven million premature deaths happening every year.

The effect of air pollution is very aggressive in human life from the origin to old age if not monitored and controlled properly. The vital growth of the fetal like the lung growth and respiratory system growth are affected by the air pollution. This leads to the increase in the level of toxicity in blood and creates severe problem to the heart and lungs. This continues throughout the childhood and enhances the chance of breathing problems like vizing, asthma. Air pollution shows severe impression on the development of impaired cognition in addition to the respiratory and cardiovascular problems [1-8]. To an individual human being who is living closer to heavy traffic areas, in poorly ventilated house, improper diet accompanying smoking and in family stressed situation, air pollution causes severe health uses and hence it needs to be analysed and controlled. As a global effect, there is a drastic change in the climate with unpredictable conditions in atmosphere which leads to the accumulation of large volume of pollutants and hole in ozone layer.

Lichens are plants that depend on another organism for its survival. There are many such kinds of organisms and some of them are fungi, photo bio ant like green alga or cyano bacterium. These organisms create a synergetic relation with each other for their living. Some of the lichens are having much complex structures as they may contain more than two organisms which are synergistically related. The lichens can help to monitor the different stages of pollution as they are capable of survive for a very long span of time [2]. The main reason advantage of using the lichens to calculate the pollution level is that, it can be done without any unique laboratory setup. The conventional methods used earlier damages the existence of the species which can be overtaken by the image processing methods that help to do the process without even touching the species.

The living organisms that respond gradually to the natural environmental changes are referred as bi- indicators. There are many gases that causes the air pollution. One main such gas in sulphur oxide and lichens serve as the bio-indicators in such environments too to identify the air pollution and its extent. This is possible with lichens, because they consume their water and the necessary nutrients from the atmosphere and not from the soil [8-15]. Hence the lichens can able to react rapidly for the air pollutants in the surrounding. Lichens are the cheap and inexpensive method that is used for analysing and evaluating the level of air pollution in the atmosphere compared to the typical and other most advanced pollution monitoring system using sensors. Lichens can able to tether the pollutants that are absorbed in the fungal threads and hence they have the enhanced ability to measure the toxic elemental pollutants and radioactive metals in the surroundings [3]. To get the exact information about the air and its pollution content, lichenologists use the lichens to analyse and measure the accumulated pollutant level in the air. Xanthoria is a family of foliose yellow lichen and is very common in nitrogen rich areas of Ireland. Xanthoria usually looks like yellow patches which grows on trees and walls. It has a light shade, which makes it to look like pale green or greyish green colour. Xanthoria uses the spores that are produced in its reproductive cups for reproduction. The varieties of colours available in Xanthoria are extraordinary that ranges from dull grey-browns to brilliant yellow or orange-red. Similar to its colour, the size of the lichens too have drastic differences which ranges from crust-like growths on rocks, wood or soil that are almost invisible to naked eyes to big rock sizes. The unique feature of the lichens is its bright colour [4].

2. Related Works

A. Effectiveness of deep learning in image classification

The images need to be executed at multilayered extent to process the information at all levels of the image and it can be done by Deep learning. It starts from the lower layer covering the local feature like small curves to the higher layer which has complex features. The training process is used to speed up the evaluating at the higher layer features [16-21]. In recent years, Deep learning gains more attention due its dominance in terms of accuracy while dealing with large amount data and features

B. Related Works

Dr. Awasthi, “Father of Indian Lichenology”, initiated the study of lichens in an efficient and standard way. His analysis on lichens of Western Ghats of India was initial published in 1957 [4], which introduced novel species to the world, like Parmelia (Hypogymnia) Pseudobitteriana (from Kodaikanal). The school oflichenology at Lucknow University arranged a team to conduct a review about the lichens of of Nilgiri and Palani Hills and to group them [8]. Negi&Upreti (2000) made an attempt to consolidate the information that have been listed as 315 and 771 lichen taxa which is mainly based on macro and microlichen keys that has been identified by Awasthi (1991). Lichens have the capability to grow in different biological situation. They can be sited in habitats like arctic to tropical rainforests where they settle in a large variety of substrates, such as rock, bark, soil and bark surfaces [5].

Now a days there is a huge increase in global warming even in the high-altitude regions which affects the lichen inhabitants harshly. For past three decades, many researchers who involved in the forest regions all over the world are deliberating over the weakening of the lichen organisms (Nayaka et al 2013a). The main reason for choosing the lichens for the air pollution monitoring is that, lichens have the capability to grow in non-polluted atmosphere as they are very sensitive atmosphere [7]. Hence, they are termed as the bio-indicators of air. The various species of lichens used to show different degree of sensitivity to air pollution. As there are so many disturbances to the environment like industrial and automobile smokes that creates change in environment like high sunshine (temperature) and less to no rainfall with relatively minimum humidity, the growth rate of the lichens is getting reduced in recent years. Human anthropogenic manners in forest is also an important factor that affects the lichen distribution. Bio-inspired algorithms are simple to implement and the complication level of the algorithm is also reduced [22-29].

Swarm intelligence algorithms have dissimilar kind based on the interaction established among the swarm agents [10]. In order to understand and analyze the unsupervised feature representation for 44 different plant species that are collected at the Royal Botanic Gardens, Kew, England, a network named Convolution Neural Networks (CNN) was proposed by Dabovet al. (2007). Experimental outcome using these CNN features with different classifiers gives better performance with uniformity and preeminence when compared to the state-of-the art solutions which depended on manually crafted features [20],[21]. The main purpose for developing the CNN model is to automatically learn the feature representation for plant categories and it was identified and diagnosed through a visualization strategy based on the DN [30], [31].

A different approach that can be employed in wide range of applications was developed by Amanpreet Kaur& Singh [32-39]. This approach was an evolutionary computing method based on colony aptitude which was a better parallel searching algorithm. Particle Swarm Optimization (PSO) was able to show a very impressive performance and when it is mutually combined with other methods, it results in a truly artificial advanced. There are also some studies going on about how the PSO could be combined with other methodologies such as neural networks, rough sets, clustering, thresholding, genetic algorithm, wavelets and fuzzy systems. The basic idea of PSO was inspired by social behaviour of bird flocking, fish schooling and swarm theory. A self-adaptive mechanism to mechanically alter the parameters of DE during the evolution and a mixed mechanic of DE and K-means was applied to strengthen the local search [40]. The arithmetical investigational results on a set of commonly used test images show that they were able to develop an algorithm which was a feasible quantization method and was able to produce better results than K-means and Particle Swarm Algorithm (PSO) for the colour image quantization. While using the DE to solve the colour image quantization, it was difficult to set their two parameters. From this it can be concluded that colour image quantization algorithm is not performed well based on Self Adaptive Differential Equation –Colour Image Quantization.

3. Deep Learning Approach for Lichen Classification

A. Dataset details

Lichens are not the simple structures like fungi. They are formed with the association of one or more races of fungi and

algae. There are 2,300 species of lichens that belongs to 305 genera and 74 families collected across different regions of India, a mega diversity region in the world. Lichens grow in various places like bark of tree, walls, rocks, gravestones, roofs and soil [3-5]. Lichens are used for the decoration purpose in indoor or outdoor of the buildings. Not just for decoration, based on the image analysis of the lichens they can be used for analysing the pollution level around the buildings. Based on the lichen community structure and the distribution of bio-indicator species, the primary information about the air quality can be retrieved. In the proposed work, to analyse the pollution around the buildings a collection of 9718 images representing the lichens with different structure and composition is used as used as a dataset (Table I).

TABLE I. DETAILS OF THE LICHEN DATASET

Dataset Details					
Image	No of Images	NP	MP	HP	EP
Total	9718	2348	2462	2396	2512
Training	7774	1878	1970	1917	2010
Testing	1944	470	492	479	502
* NP – Not Polluted; MP – Moderately Polluted; HP – Highly Polluted; EP – Extremely Polluted					

In the proposed work, the lichen collections are used to indicate four different pollution levels, which makes the proposed work as a multiclass classification approach. The images representing the different pollution levels are visually presented in Fig. 1.

Fig. 1. Different variations of Lichen affected by Pollution

B. RESNET - A Deep Learning approach for image classification

Lichen analysis for pollution identification is a multiclass image classification problem. RESNET is a CNN based DL approach proposed for image classification. RESNET is one of the early adopters of batch normalization. RESNET-50 is with 25Million parameters. RESNET is the architecture that supports hundreds and more convolution layers. It is the first architecture to make identity mapping by using skipped connections . Working of RESNET architecture is represented in following Fig. 2.

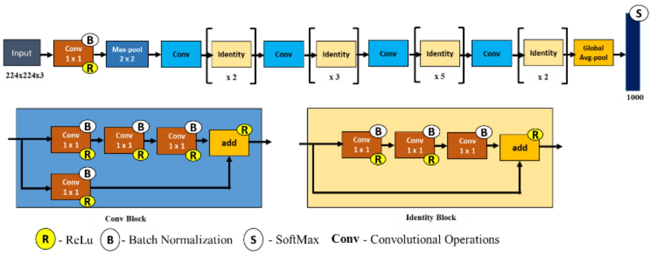

Figure 2. Basic RESNET Architecture

The basic building block for RESNET are the convolution and identity blocks. Convolutional block depends on ReLU activation function and batch normalization. Finally, the model converges by using softmax activation function. With this architecture it is possible to design deeper CNNs up to 152 layers without compromising Model's generalization power.

Lichen classification is a two-step process. Step 1 concentrates on learning the set of features from the input images. Step 2 receives and the flatten output of step 1.

C. Pollution Detection model using RESNET Architecture

The overall pollution detection around the smart buildings starts with the configuration of RESNET architecture. Since Lichens has the ability to grow on rocks, walls and roofs it is proposed to use Lichens as a pollution indicator around the buildings. There exists around 2300 species of lichens with various physical and chemical composition used to indicate the pollution level in their surroundings. Lichen can be placed around the buildings and the same can be monitored using Unmanned Ariel Vehicles. The images captured are given as an input to the RESNET Lichen classification model.

The proposed RESNET model is capable of receiving the input and extracting the colour features out of the images. The extracted features pass through the stack of convolution and max pool layers in RESNET architecture. Finally, the input image is flattened and classified based on the pollution level.

The performance of the RESNET model is validated with the test data and with the other already existing machine learning models shown in Fig. 3. In this work we have implemented two most familiar machine learning models namely SVM and VGG-16. RESNET performs better in terms of all the performance measures when compared with the other machine learning and deep learning models. The detailed performance of the proposed work is discussed in the section 5.

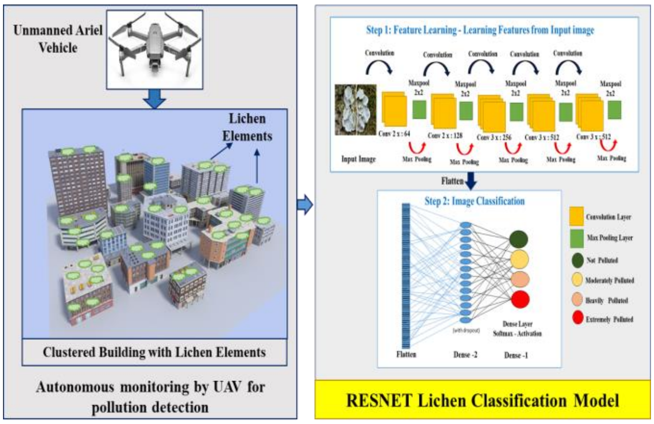

Fig. 3. Pollution Detection Model using RESNET

4. Results and Discussion

This section discusses the overall performance of deep learning and machine learning models used in lichen classification for the process of pollution detection.

A. Performance Comparison of DL with ML Models

The confusion matrix given in Table II includes all the performance measures namely accuracy, precision, recall and F-Measure. Confusion matrix comparing the true labels and predicted labels is represented in the below Fig. 4.

Table II. Confusion matrix

Algorithm	TP	TN	FP	FN
SVM	762	816	174	192
VGG16	906	915	54	69
RESNET	920	933	40	51

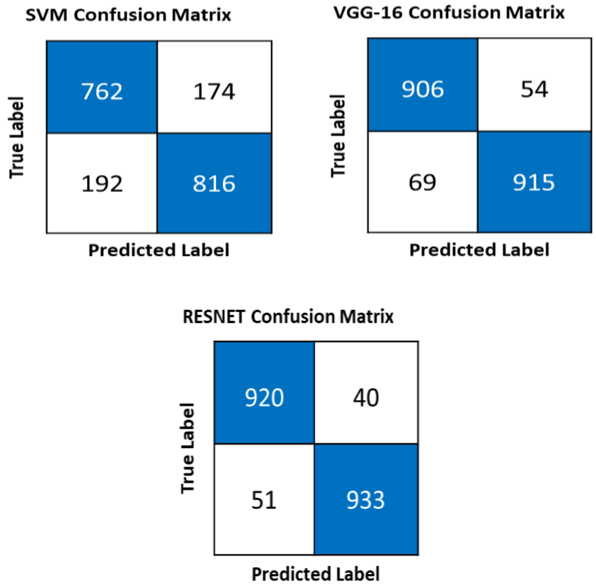

Fig. 4. Confusion Matrices

The performance measures mentioned in Table. III are calculated from the values given in the confusion matrix represented in Table III using the equations (1), (2), (3) and (4) given below. The visual representation of performance of all the algorithms is

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

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

$$\text{F1 Score} = 2 * \frac{\text{Recall}*\text{Precision}}{(\text{Recall}+\text{Precision})}$$

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

Table III. Performance Measures

Algorithm	Accuracy	Precision	Recall	F-Measure
SVM	81.2	81.4	79.9	80.6
VGG1	93.6	94.4	9	93.6

6			2.9	
RESN ET	95.3	95.8	9 4.7	95.3

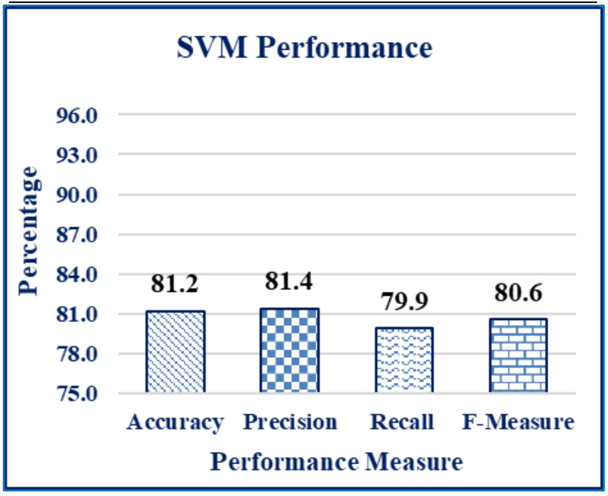

Fig. 5. SVM Performance

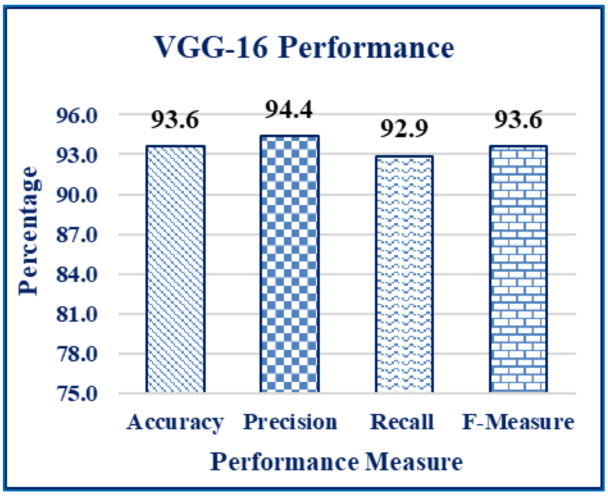

Fig. 6. VGG-16 Performance

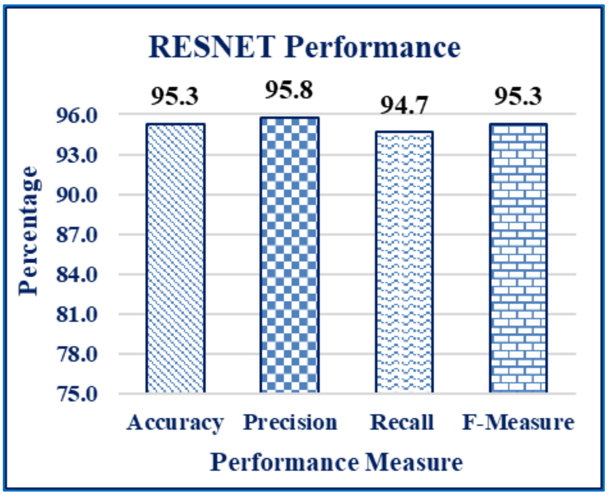

Fig. 7. RESNET Performance

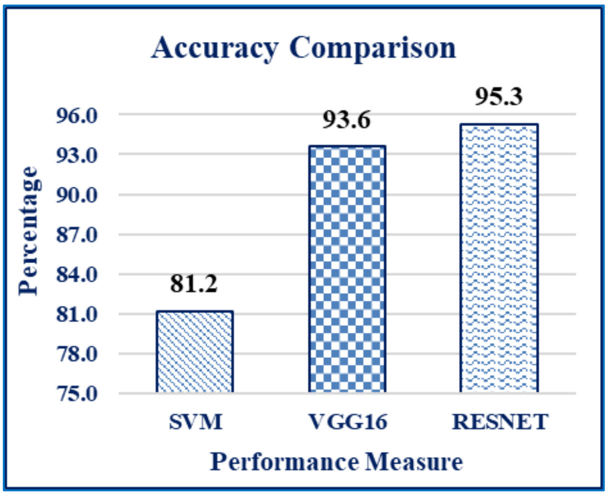

Fig. 8. Accuracy Comparison

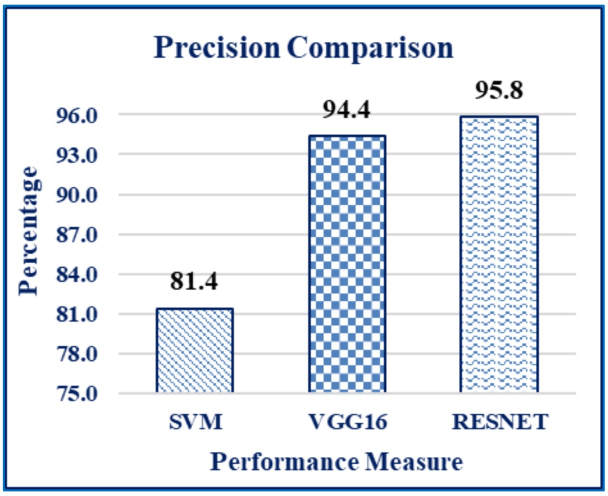

Fig. 9. Precision Comparison

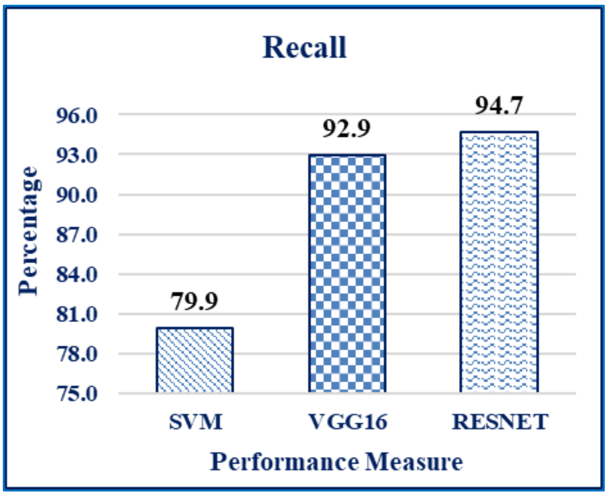

Fig. 10. Recall Comparison

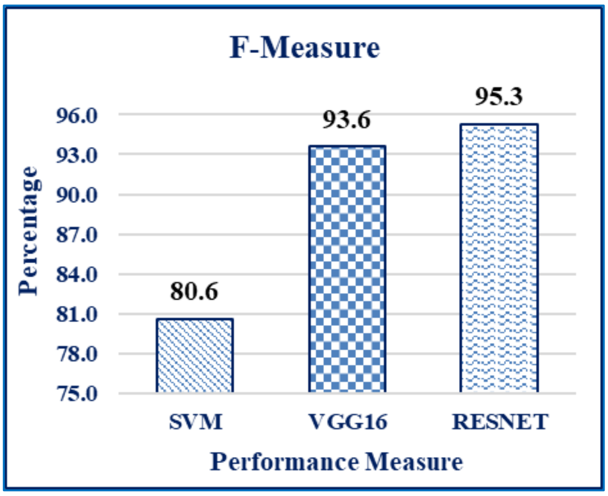

Fig. 11. F-Measure Comparison

Compared with the SVM and VGG-16 algorithms RESNET based deep learning algorithm correctly classified the maximum number of images. RESNET produces the highest accuracy of 95.3 % whereas the accuracy of SVM and VGG-16 are 81.2% and 93.2% respectively. VGG-16 can exactly learn the features from the input images when compared with SVM. Even though SVM is one of the best multi class classifier, where number of features for each data point exceeds the number of training data sample, the SVM starts underperforming. RESNET performs better in terms of other parameter measures like precision, recall and F-Measure and produces the maximum values of 95.8 %, 94.7% and 95.3% respectively. RESNET performs better multiclass classification then the other deep learning and machine learning models.

B. Performance Analysis of RESNET with VGG-16

RESNET is a deep architecture with 16 layer stacks of convolution and maxpool layers. Input lichen images are grouped separately for training and for model validation. The overall performance of RESNET in Table IV and VGG-16 in Table V are measured in terms of accuracy and loss functions.

Table.IV RESNET Performance

RESNET Performance				
Epoch	***Training Accuracy***	***Validation Accuracy***	***Training Loss***	***Validation Loss***
5	0.71	0.70	0.56	0.51
10	0.84	0.82	0.35	0.31
15	0.85	0.84	0.21	0.17
20	0.89	0.88	0.13	0.09
25	0.93	0.94	0.07	0.06
30	0.93	0.94	0.05	0.04
35	0.93	0.94	0.04	0.02
40	0.95	0.95	0.02	0.01
45	0.95	0.95	0.02	0.01
50	0.95	0.95	0.02	0.01

Table. V VGG-16 Performance

VGG-16 Performance				
Epoch	***Training Accuracy***	***Validation Accuracy***	***Training Loss***	***Validation Loss***
5	0.58	0.69	0.81	0.73
10	0.83	0.84	0.56	0.45

15	0.85	0.86	0.26	0.19
20	0.89	0.89	0.13	0.09
25	0.93	0.93	0.09	0.08
30	0.93	0.94	0.08	0.03
35	0.93	0.94	0.04	0.02
40	0.94	0.94	0.02	0.01
45	0.94	0.94	0.02	0.01
50	0.94	0.94	0.02	0.01

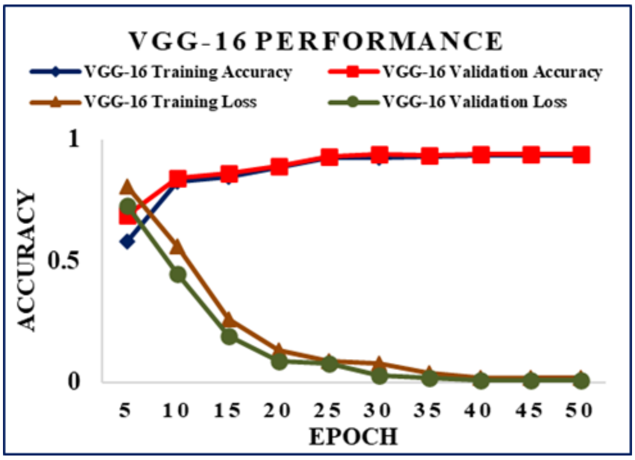

Fig. 12. VGG-16 overall Performance

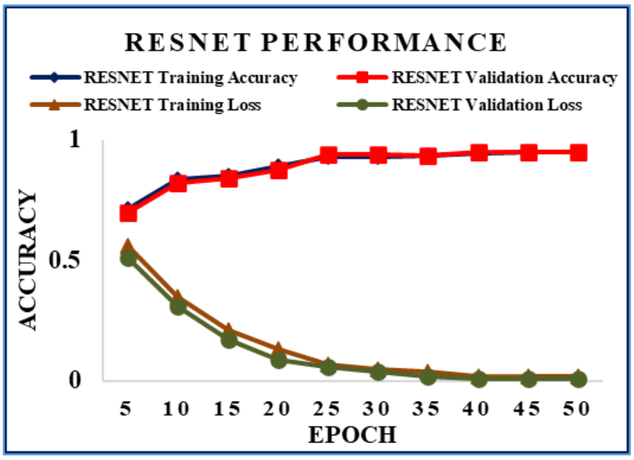

Fig. 13. RESNET overall Performance

The visual representations of the performance of VGG-16 and RESNET are mentioned in Figure 12 and Figure 13 respectively.

5. Conclusion

The RESNET algorithm produces the maximum training accuracy of 95.3% and validation accuracy of 95.1%. The model can able to produce the stabilized accuracy at the epoch value of 25 and stabilized loss value at the epoch 20. This clearly shows the stability of the model. In addition the RESNET model produces the maximum accuracy at 40th epoch and minimum loss value at 45th epoch. Thus the technological advancements in the deep learning algorithms in the area of image classification can be used for lichen image classification. This application can be extended for the process of pollution detection in the smart city implementation projects.

6. Acknowledgement

This work was supported by Korea Research Fellowship Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (No. 2019H1D3A1A01101442). This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea Government (MSIT) (No. 2019R1G1A1095215)

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