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Review

Medicinal Plant Identification using Gabor Filters and Deep Learning Techniques: A Paper Review

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Abstract: Computer-aided identification of plants is a branch of machine learning that has become more recognized recently and proves itself as a vital tool in numerous sectors including pharmacological science, forestry and agriculture. This has essentially generated a zeal in creating automated systems for the identification of diverse species of plants. This study reviewed plant species classification relying on leaf textural features using Gabor filters and revealed that Gabor filters perform better when combined with other feature extraction methods. Therefore, this study proposes using Log-Gabor filter in the field of plant identification to improve accuracy since they overcome the drawbacks of Gabor filters which are; the maximum bandwidth of a Gabor filter is limited to approximately one octave and Gabor filters are not optimal if one is seeking broad spectral information with maximal spatial localization.

Keywords: Plant Identification, Gabor Filter, Log-Gabor Filter, Deep Learning, Texture

Introduction

Plant taxonomy studies how to find, identify, describe, classify and name plants. Many techniques have evolved towards plant taxonomy over the years. These include chemotaxonomic classification, anatomical classification and morphological classification. The morphological and anatomical are seen as a more traditional means of classification as compared to chemotaxonomy (Simpson, 2019).

Although Ghana's tropical vegetation is rich in medicinal plants, knowledge of their distribution and uses appear to be the preserve of the elderly and, particularly the herbalists (Adeniyi *et al*., 2018). Most of whom acquired this knowledge through oral transmission or as a result of using the plants in traditional medicine preparation. Generally, information gathered on the diversity and importance of plants with medicinal properties in Ghana and their usage has only been made known by some individual researchers (Addo-Fordjour *et al*., 2011; Boadu and Asase, 2017) through ethnobotanical means. Globally, the acceptance and utilization of herbal medicine are on a constant rise. This situation is no different in Africa where over 60% of the population depend directly on plants for their primary healthcare requirement-particularly in the developing countries. This makes plants a major contributor to natural products and forms an important part of health care. The pharmaceutical industry depends greatly on traditional medicines; thus globally, a quarter of all prescribed drugs are as a result of the extraction from these medicinal plants. Thus, medicinal plants are preferred owing to the significantly lower adverse reactions and being economical in comparison with synthetic drugs (Pushpanathan *et al*., 2020). Classifying plants with medicinal properties are beneficial in many ways to humans therefore it has been of importance to address this problem (Barimah and Akotia, 2015).

The use of plants as medicine has generated the need for plant identification to determine whether a particular plant is of medicinal use or not. Also, it is easy to confuse two different plants when closely looked at by untrained eyes. This makes plant identification a very crucial aspect that cannot be taken lightly in the field of natural products and medicine as misidentification can bring potentially serious consequences (Boadu and Asase, 2017). Using conventional keys (i.e., scientific names) to identify plants is complex, time-consuming, tedious for non-botanists and creates a daunting challenge for freshmen interested in acquiring specific knowledge (Wäldchen and Mäder, 2018). Using the diverse morphological characteristics of plants to distinguish between them is a challenging task. These challenges are mainly high intra-class variability and small inter-class differences (Šulc and Matas, 2017). Plant categories are closely related and often

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exhibit some level of relationship between some of their structural parts leading to low inter-class differences. Plants also show a difference in shape characteristics due to environmental influences such as climate change, topographical location etc. (Sfar *et al*., 2013). This makes plants broadly different in size, shape, color and texture with varying appearance throughout the year leading to high intra-class variations (Lasseck, 2017). With the swift advancement of metabolite- related databases (KNApSAcKCoreDB), data mining tools have been suggested to investigate the systematics value of metabolite-content of plants (Afendi *et al*., 2012).

Gabor filters are widely applied in many areas like palmprint identification (Zhang *et al*., 2003), fingerprint identification (Areekul *et al*., 2005) vehicle detection (Sun *et al*., 2002), facial expression (Barbu, 2010), image classification and disease detection (Qian *et al*., 2003; Sahebrao *et al*., 2015; Zheng, 2010). Gabor filters also found their application in plant identification (Cope *et al*., 2010; Tang *et al*., 2003; Venkatesh and Raghavendra, 2011) and plant disease identification (Patil and Kumar, 2017; Yang *et al*., 2019).

Studies have revealed two shortcomings of Gabor filters. The first concern is with the limitation on the maximum bandwidth which is set to one octave and the second issue is the presence of the nonzero DC element in the even-symmetric filter open bandwidths. Hence, Gabor filters would not be the go-to option for research that seeks to achieve broad spectral details with maximal spatial localization (Wang *et al*., 2008). Log-Gabor function serves as an alternative function to the Gabor function (Arrospide and Salgado, 2013).

Literature Review

Plant Identification

Plants in general are recognizable by their features such as leaves, fruits, flowers or plants as a whole. Out of all the keys of identification, the most promising and effective means of medicinal plants identification is the use of the leaves (Ab Jabal *et al*., 2013; De Luna *et al*., 2017; Lee *et al*., 2016; Pushpanathan *et al*., 2020; Wäldchen and Mäder, 2018; Yigit *et al*., 2019).

The term texture is used in describing an object or phenomenon surfaces. It is the essential feature used in pattern recognition in computer vision undoubtedly (Zhang *et al*., 2012). Texture analysis is utilized in extracting features in an image for recognition. Texture in this case, refers to an image's spatial arrangement of intensities. Thus, texture extraction becomes the quantification of the connections of the intensities' spatial arrangement. In the identification and classification of plants, the leaf texture plays a key role. Fractal Dimensions (FracDim), Gabor Filters (GF) and Gray-Level Co-occurrence Matrix (GLCM) are some popular techniques for characterization of leaf texture towards plant identification (Casanova *et al*., 2009; Kadir *et al*., 2011a). Texture analysis involves four basic methods and they are Statistical methods (First Order Statistics, Second Order Statistics, Auto correlation etc.), Geometrical methods (Morphological methods, Pattern spectrum, etc.), Model based methods (Random Mosaic Model, Autoregressive Model, Fractal Dimension, etc.) and Signal processing methods (Eigen Filters, Fourier Domain Filtering, Gabor Filter, etc.) (Armi and Fekri-Ershad, 2019). Signal processing methods used in texture characterization over time have proven a great tool (Stepień, 2014) since they are able to extract features using the first and second order statistics as well as collect the dispersal of filter responses (Nava *et al*., 2011).

Plant morphology studies the external textures and the physical form of plants (such as the leaf, flower, bark, stem etc.) while the studying of the internal plant structure which usually occurs at the microscopic/cellular level is referred to as plant anatomy. Classification systems in plants have seen an extensive improvement possibly owing to the morphological characteristics of plants which have become the basis and framework for advances in taxonomy. The science of chemotaxonomy aids in classifying plants using their chemical constituents. In any living organism, it is obvious that the primary metabolites produce secondary metabolites. These metabolites have a chemical structure and a biosynthetic pathway which becomes explicit and constricted to organisms that are taxonomically related and thus enhancing their classification (Lou *et al*., 2021).

Traditional chemosystematics of plants considers the absence or presence of various metabolites (Singh, 2016; Wink, 2003). This approach borders on the hypothesis that selected secondary metabolites dominate within a given taxon. Chemosystematics in plants has initially been used to establish the differences in other organisms and plants recognition which is to be avoided and those beneficial for food. The insight from this has gradually been made official using harmful, inactive and useful chemical constituents from significant taxa presently recognized and recorded. Plant chemosystematics could reveal the universally known natural history of plants taking cognizance of its interaction with the environment and similar plants (Christenhusz, 2020; Reynolds, 2007; Singh, 2016).

In recent years, although the chemotaxonomy approach has fast developed, yet the traditional method for classifying plants using their comparative external morphological characters remains essential to systematics and it dominates other forms of taxonomic features used in plant classification owing to reasons such as; the easily observable morphological characters; because they have innumerable variations, they assist in identification and delimitation; one is not required to obtain a sophisticated laboratory arrangement to assess these morphological characters. To study anatomical features of plants, one would require possibly a light microscope or a hand lens or a dissecting microscope as well as effort and time to harness information from sources such as molecular biology and photochemistry ensuring the merit of morphological characters against the other forms of plant taxonomy.

The KNApSAcKCoreDB is useful in multifaceted plant research as an extensive plant-metabolite relation DB. These researches could be on systems biology, bioinformatics, construction of integrated DBs and identification of metabolites (Ikeda *et al*., 2013; Nakamura *et al*., 2014) and also a potential source of advanced metabolites contents of plants (Shinbo *et al*., 2006). The KNApSAcK Family database systems have seen several usages of metabolomics studies. For example, previously the KNApSAcK Family DB systems have been deployed to appreciate the medicinal utilization of plants based on modern and traditional knowledge (Afendi *et al*., 2013; Wijaya *et al*., 2014).

There has been a study of several methods for recognizing plants by studying their leaf texture, shape, color and venation. Some of the methods include Gabor Filters (GF), Fractal Dimensions (FracDim), Gray Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradient (HoG) for leaf texture; (Backes and Bruno, 2009; Casanova *et al*., 2009; Cope *et al*., 2010; Kebapci *et al*., 2011; Rossatto *et al*., 2011; Sá *et al*., 2013; Syahputra *et al*., 2014; Zhai and Du, 2008), Simple and Morphological Shape Descriptors (SMSD), Hu moments, Fourier Descriptor (FD), Tchebichef Moment Invariant (TMI), Centroid Contour Distance (CCD), Zernike Moment Invariant (ZMI), Harmonic mean projecting transform for leaf shape; (Aakif and Khan, 2015; Chaki *et al*., 2015b; Du *et al*., 2007; Hossain and Amin, 2010; Kadir *et al*., 2011b; Lee and Chen, 2006; Teng *et al*., 2009; Zahra *et al*., 2020), Color Moments (CM), Color Histograms (CH), Color Co-occurrence Matrices (CCM) for leaf color; (Caglayan *et al*., 2013; Che Hussin *et al*., 2013; Kebapci *et al*., 2011; Prasad *et al*., 2013; Yanikoglu *et al*., 2014). Areoles morphology, Leaf vein and Run-length features for leaf venation; (Gu *et al*., 2005; Larese *et al*., 2012; Larese *et al*., 2014a; 2014b)

Deep Learning

An extensive family of machine learning techniques is deep learning and it is grounded on learning data observations. Deep learning architectures like convolutional Deep Neural Networks (DNN), recurrent neural networks and deep belief networks have been employed in sectors such as natural language processing, computer vision, bioinformatics, audio recognition and automatic speech recognition, having produced remarkable outcomes on several works. This concept has been categorized as a buzzword for neural networks (Benuwa *et al*., 2016; Gomes, 2014). For learning tasks that require supervision, applying deep learning techniques removes feature engineering via the translation of the data into compact intermediate forms similar to principal components and this minimizes redundancy in representations as it derives layered structures (Deng and Yu, 2013). Numerous deep learning models are used in unsupervised learning problems, thus, offering a significant advantage since untagged data is normally (generally) in abundance than tagged data. Deep belief network is one of the deep frameworks used in an unsupervised form (Bengio *et al*., 2013). DNN is generally interpreted in terms of the Universal approximation theorem or Probabilistic inference (Hinton *et al*., 2006; Murphy and Murphy, 2012).

In current years, the development of Convolutional Neural Network (CNN) has proved to be an efficient identification technique and gathered widespread attention. CNN now has become one most effective techniques in the pattern classification and image processing fields (Krizhevsky *et al*., 2017; Lecun *et al*., 2015) and is relatively preferred over conventional techniques such as the supervised and unsupervied learning techniques (Chatfield *et al*., 2011) by verifying on a wide scale. CNN replicates the visual cortex of humans and it's the choice of neural network for computer vision (image and video recognition). The brain's visual cortex comprises discontinuous layers of both complex and simple cells and inspires CNN modelling. CNN is also adopted in other areas such as Natural Language Processing (NLP), drug discovery, etc.

Architectural designs of CNN appear in many forms; but, generally, they constitute grouped pooling (subsampling) and convolutional in modules. The pooling layers function to minimize the feature maps' spatial resolution and so attain spatial invariance to input translations as well as input distortions (Lecun *et al*., 2015; Ranzato *et al*., 2007). The pooling layer is utilized in minimizing the spatial size or image's resolution and the number of parameters hence reducing the computation burden. This is shown by minimizing the number of links between the convolutional layers (Gu *et al*., 2018). There are usually alternations between the pooling layers and convolutional layers. Max pooling and Average pooling are the commonest types of pooling. Individual CNN comprises a dissimilar number of convolution layers relying on network requirements. The low level such as edges, corners are learnt by the initial convolutional layers which are passed to the other convolutional layers to acquire higher-level features. Convolutional layers functions for feature extractors, hence, the feature representations of the input images are learnt by the layers. Within a feature map, all the neurons are constricted to have their weights equalized; nonetheless, within the same convolutional layer, different feature maps possess varying weights, thus enabling the

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extraction of many features are each location (Lecun *et al*., 2015; Yu *et al*., 2014). Formally, it is computed below as the kth output feature map Y_k:

$$Y_k = f\left(W_k * x\right) \tag{1}$$

where, "x" denotes image input; "W_k" represents the coiled filter linked to the kth feature map, the two-dimensional convolutional operator is symbolized by the multiplication sign(*), the inner product of the filter model is expressed separately at every location of the input image; as the nonlinear activation function is also shown by $f(\cdot)$ (Yu *et al*., 2014).

Related Works

Gabor filters when combined with other texture analytical techniques were found to provide better performance. Tan and Triggs (2007) extracted features from the images using Gabor and LBP and then dimensionality reduction was performed using Principal Component Analysis (PCA) method. After normalization, all the extracted features were fused and then classified.

Introduced new Gabor filter banks specifically made to identify plant species using their bark texture features. In this method, the texture was constructed as several narrowband signals separated using their normalized ratios of amplitudes and central frequencies. To integrate the narrowband signals, the normalized ratios of amplitude were used as an energy weight. This model used allowed for a collection of features of the bark texture which was obtained from every kind of plant bark assisting the design of the equivalent Gabor filter bank while differentiation of plant was made possible.

Lin *et al*. (2008) performed a joint analysis of Gabor filter and LBP for classification of plant leaves. A database of about 500 leaf images corresponding to 27 categories was used with a filter bank of 20 filters (5 scales and 4 orientations). An accuracy of 85.44% was achieved.

Casanova *et al*. (2009) using a Gabor bank of 64 filters (8 rotation filter and 8 scale filters) found out that Gabor filter outperformed FD and GLCM after using it on leaf lamina and margins. Other authors also found out that a combination of Gabor filter and GLCM performed better than using them individually (Chaki *et al*., 2015a; Cope *et al*., 2010). Venkatesh and Raghavendra (2011) proposed a combination of Gabor filter with the Local Binary Pattern (LBP) descriptor and found out that it performed better than using them individually. Gabor filter had a higher discriminatory power after comparing it to Histogram of Oriented Gradient for texture analysis (Yanikoglu *et al*., 2014).

Plant leaf identification using Gabor filters (Tang *et al*., 2003; Venkatesh and Raghavendra, 2011) was performed to analyse features in the spatial domain at different orientations and frequencies. Gabor filters and Co-occurrence matrix was used in combination for plant identification by Cope *et al*. (2010).

Backes *et al*. (2009) after numerous tests performed achieved the best results of 82.93% using a family with 64 filters (eight rotations and eight scales). Patil and Bhagat (2016) used Gabor features to extract leaf texture features. Using the UCI Machine Repository Dataset, 85% was accuracy was used whiles 94.1% accuracy was achieved using Swedish Leaf Dataset.

Cope *et al*. (2010) proposed a technique for plant texture classification based on joint distribution of Gabor filter responses using a filter bank of 128 filters. This method achieved excellent recognition rate of 95% on Brodatz dataset and was also effective in the case of laborious task of plant classification based on leaf analysis.

Alamoudi *et al*. (2020) used a number of texture-based features including Gabor and Laplacian of Gaussian filters followed by the Grey Level Co-occurrence Matrix to generate leave image features. The proposed method achieved about 93.7% accuracy. Wang *et al*. (2020) presented a novel counting-based leaf recognition method based on the elliptical half Gabor wavelet and maximum gap local line direction patterns. Leaf database used was the Swedish, Flavia and ICL database. The half Gabor achieved an average of 85% on all databases.

Several authors have used neural networks and also CNN in particular for plant identification. Jassmann *et al*. (2015) developed a mobile application for classifying plants using CNN based on the nature of the leaf using the Image CLEF data set. The architecture proposed consisted of a layer that is convoluted, followed by a composite layer and two fully connected layers applied to the 60 × 80-pixel input image. Bao *et al*. (2019) proposed a system using two methods (Histogram of Oriented Gradient (HoG) and deep convolutional neural network) for the problems concerning identifying plants using their leaf patterns. HoG was used in classifying the features and CNN for identification purposes. Adetiba *et al*. (2021) leveraged on five pre-trained CNN models (Alex Net, Goog LeNet, VGG-19, ResNet50 and MobileNetV2) and Leaf snap image dataset of 185 plant species to empirically develop an accurate plant species recognition. Among the pre-trained models, MobileNetV2 with ADAM optimizer gave the highest testing accuracy of 92.33%.

Even though Gabor filters provide promising results when it comes to plant identification using texture, it was seen that performance increases when Gabor filters are combined with other features like color, shape, venation and other texture feature extraction methods such as the LBP and GLCM. In (Casanova *et al*., 2009), using a combination of Gabor filter and Gray Level Co-occurrence Matrix (GLCM) to model the texture of plant leaf, the accuracy of the model increased form 81.6 to 97.6% when texture model was combined with shape features. Also, using a combination of Gabor filters and Local Binary

Patterns (LBP), the accuracy of the model increased from 85% using only Gabor filters to 90% (Lin *et al*., 2008). In Patil and Bhagat (2016), the performance of the model also improved from 94% when using Gabor filters to 96% when combined with GLCM using the Swedish leaf dataset and 85 to 88% and using the UCI Machine Repository Dataset.

The parameters of Gabor filters which includes the filter size, standard deviation, scale and orientation influence the accuracy of the model. To achieved best results, a combination of the parameters must be investigated to provide the best results. Another limitation in using Gabor filters is that, rotation and scaling greatly influences the identification process. Therefore, Gabor filters must be defined to cover all possible orientations.

Lastly, there is a high computational cost due to using filter banks required in Gabor filters. This can be mitigated by using feature selection or reduction methods like the Principal Component Analysis (PCA).

Methodology

Gabor Filter

One of the processing signal techniques for the extraction of texture is the Gabor filter. Gabor filters are wavelets band in which individual wavelet captures energy at a particular direction and frequency. Its operation uses a local band having a known optimal localization pass filter features in both the frequency domain and the spatial domain. Gabor functions were first proposed by Dennis Gabor (Rai and Rivas, 2020). These filters have obtained immeasurable attention over the years. This is due to the fact these filters can estimate certain visual cortex cells of some mammals. Gabor filters' orientation and frequency representations are closely related to that of the human visual system and they are found to be significantly suitable for textural representation and discrimination. Also, these filters are known to have optimal localization properties present in frequency and spatial domain, hence making it best suited for problems with texture segmentation. These filters should be considered a sinusoidal plane of a certain orientation and frequency, thus Gabor filters are orientation-sensitive.

A Gabor filter has both frequency-selective and spatial-selective properties together with optimal joint resolution in both frequency and spatial domains (Munawar *et al*., 2021). These functions shown by the product of a sinusoid and Gaussian function constitute a single family of linear filters that behave optimally in the sense that their simultaneous resolution in both domains is maximal (Rai and Rivas, 2020). Specifically, using a Gabor filter in texture analysis was motivated due to the studies of Daugman on visual modeling of simple cells based on the experimental findings on the orientation selectivity of visual cortical neurons previously observed by Hubel and Wiesel in human beings and cats (Hubel and Wiesel, 2012; Kong, 2009).

A two-dimensional Gabor function is defined as a sinusoidal wave multiplied by a Gaussian function in a complex number form (Yuan *et al*., 2020):

$$g_{\Theta}(x,y) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x'}{\lambda}+\phi\right)\right) \tag{2}$$

Thus:

$i =$ Imaginary unit and $\Theta = \{\lambda,\theta,\phi,\sigma,\gamma\}$ is the parameter:

$$x' = x\cos(\theta) + y\sin(\theta)$$
$$y' = -x\sin(\theta) + y\cos(\theta)$$

There are five parameters in Gabor function and each of them has a specific meaning and every parameter can take values in a specific range:

- Orientation (θ)
  θ specifies the orientation of the Gabor filter generated by the Gabor function. Valid values are real number between 0 and 2π
- Wavelength (λ)
  λ represents the wavelength of the Gabor filter and its values is specified in pixels. Generally, valid values of λ are real number equal or greater than 2
- Phase offset (φ)
  φ is the phase offset in the argument of the sine or cosine factor in the Gabor function. Its valid values are real numbers from −π to π. The values 0 and π correspond to center-symmetric 'center-on' and 'center-off' functions, respectively, while −π/2 and π/2 correspond to anti-symmetric functions
- Aspect ratio (γ)
  γ shows the ellipticity of the support of the Gabor function. When γ <1 the support is elongated in orientation of the parallel stripes of the function and when γ = 1, the support is circular. Generally, it takes real values that are greater than 0 and less or equals than 1, so its range is (0,1]
- Generate σ from bandwidth b
  Parameter σ is the standard deviation of the Gaussian factor of the Gabor function. Since λ and σ are not independent argues that σ cannot be rightly stated and can only be generated via b, the bandwidth where it satisfies $\frac{\sigma}{\lambda} = \frac{1}{\pi}\sqrt{\frac{\log 2}{2}}\,\frac{2^b+1}{2^b-1} \triangleq \hat{b}$

Log Gabor Filter

Gabor transforms over-represent the low-frequency components and under-represent the high-frequency components. Log-Gabor function when viewed on a logarithmic axis has Gaussian transfer functions having frequency-response functions synonymous in several cortical cells. Again, this filter provides an extension with null DC elements, thereby arbitrarily large bandwidths are allowed to be created. A comparison of the Log-Gabor filters with the Gabor Filters shows that as Log-Gabor filters are formed using arbitrary bandwidth with the minimal spatial extent optimization feature while permitting the reduction of over-representation of low frequencies. It is also meaningful that measurements on mammalian visual systems indicate we have cell responses that are symmetric on the log frequency scale as the Log-Gabor function. Hence, the postulation on the log-Gabor functions should have the ability to encode natural images through an enhanced representation of the higher frequency constituents if the function has extended tails at the high frequency ends. Furthermore, a log-Gabor Filter always has a null DC component and therefore, the filter bandwidth can be optimized to produce a filter with minimal spatial extent. Gaussian transfer functions can be observed in Gabor functions from the perspective of the linear frequency scale; as Log-Gabor functions also shows the same features when viewed using the logarithmic frequency scale. Owing to the individuality in the log function at origin, a two-dimensional Log-Gabor filter is built in the frequency domain. Using polar coordinates system divides the filters into two components: The angular filter and the radial filter.

The frequency response of the angular filter is given by:

$$G_\theta(\theta) = \exp\left(-\frac{\left[\theta - \theta_0)\right]^2}{2.\sigma_\theta^2}\right) \tag{3}$$

and the frequency response of the radial filter can be described by:

$$G_r(r) = \exp\left(-\frac{\left[\log(r/f)_0\right]^2}{2.\sigma_r^2}\right) \tag{4}$$

The two components are multiplied together to construct the overall Log-Gabor filter which has the transfer function as:

$$G(r,\theta) = G_r(r).G_\theta(\theta) \tag{5}$$

where, σ_θ determines the angular bandwidth, σ_r determines the scale bandwidth, θ_0 is the orientation angle of the filter, f_0 is the center frequency of the filter and (r, θ) represents the polar coordinates.

The frequency response of log-Gabor filters in polar coordinates is given by (Nixon and Aguado, 2020):

$$LG_{m,n}(f,\theta) = \exp\left\{-\frac{\left(\log(f/F_m)\right)^2}{2(\log\beta)^2}\right\}\exp\left\{-\frac{\theta-\theta_n}{2\sigma_\theta^2}\right\} \tag{6}$$

The proposed framework is seen in Fig. 1.

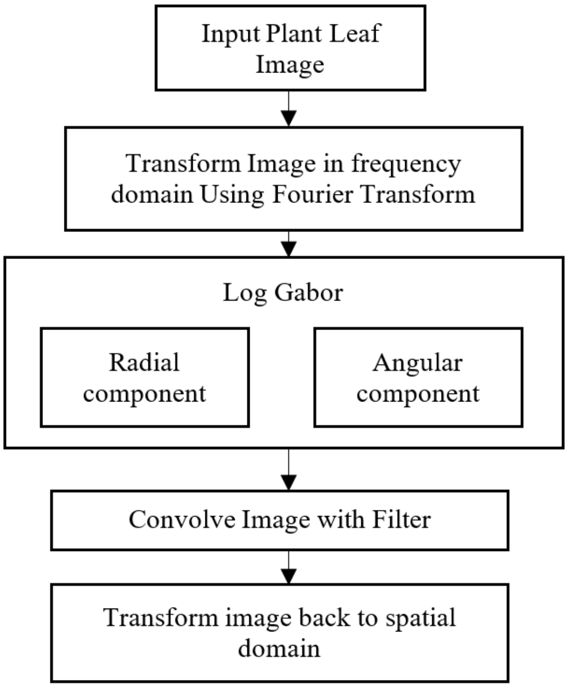

Fig. 1: Proposed framework

Table 1: Areas gabor filters have been applied

Area	References
Palmprint identification	Zhang *et al.* (2003)
Fingerprint identification	Areekul *et al*. (2005)
Vehicle detection	Sun *et al.* (2002)
Facial expression	Barbu (2010)
Image classification and disease detection	Qian *et al*., (2003); Zheng, (2010)
Plant identification	Cope *et al*. (2010); Tang *et al*., (2003);
	Venkatesh and Raghavendra, (2011)
Plant disease identification	Patil and Kumar (2017); Yang *et al*., (2019)

Table 2: Various methods for plant leaf classification

Feature	Method	References
Texture	Gabor Filters (GF), Fractal Dimensions (FracDim), Gray Level Co-occurrence Matrix (GLCM), Histogram of Oriented Gradient (HoG)	(Backes and Bruno 2009; Casanova *et al*., 2009; Cope *et al*., 2010; Kebapci *et al*., 2011; Rossatto *et al*., 2011; Sá *et al*., 2013; Syahputra *et al*., 2014; Zhai and Du, 2008)
Shape	Simple and Morphological Shape Descriptors(SMSD), Hu moments, Fourier Descriptor (FD), Tchebichef Moment Invariant (TMI), Centroid Contour Distance (CCD), Zernike Moment Invariant (ZMI), Harmonic Mean Projecting transform	(Aakif and Khan, 2015; Chaki *et al*., 2015b; Du *et al*., 2007; Hossain and Amin, 2010; Kadir, Nugroho *et al*., 2011; Lee and Chen, 2006; Teng *et al*., 2009; Zahra *et al*., 2020)
Color	Color Moments (CM), Color Histograms (CH), Color Co-occurrence Matrices (CCM)	(Caglayan *et al*., 2013; Che Hussin *et al*., 2013; Kebapci *et al*., 2010; Prasad *et al*., 2013; Yanikoglu *et al*., 2014).
Venation	Areoles morphology, Leaf vein and Run-length features	(Gu *et al*., 2005; Larese *et al*., 2012; Larese *et al*., 2014a; 2014b)

Table 3: Summary of reviewed papers

No.	Dataset	Filter bank	Accoracy	Reference
1	The Pl@ant Leaves dataset	64 filters	43.66%	Casanova *et al*. (2009)
2	N/A	64 filters	82.93%	Backes *et al*. (2009)
3	Brodatz dataset	128 filters	85.16%.	Cope *et al*. (2010)
4	Flavia dataset	N/A	87.1%	Chaki *et al*. (2015a)
5	UCI machine repository dataset, swedish leaf dataset	N/A	94%	Patil and Bhagat (2016)
6	Swedish, Flavia and ICL dataset	N/A	85.73	Wang *et al*. (2020)
7	N/A	N/A	93.7%	Alamoudi *et al*. (2020)

Analysis

Gabor filters are widely applied in many areas as shown in Table 1. There has been a study of several methods for recognizing plants by studying their leaf texture, shape, color and venation as shown in Table 2. A summary f reviewed indicates Gabor filters generally have a high accuracy rate. The dataset commonly used were the UCI Machine Repository Dataset, Swedish Leaf, ICL dataset and The Pl@ant Leaves dataset. Lastly, a filter bank of between 64 and 128 were used most often.

Conclusion

Automated identification of plant species is a subject propelled by researchers who have expertise in computer learning, computer vision and multimedia information retrieval. Even though the shape of a leaf is the most discriminative or more dominant character for leaf classification, the texture also has high importance since it can reveal or capture complementary information. Additionally, plants can be easily identified just with a portion of the leaf without the entire shape or color of the leaf using leaf texture analysis. Hence, researchers and botanists can benefit greatly from texture analysis in identifying damaged plants. Specifically, the texture depicts leaf venation details and other eventual directional features and predominately permits the description of micro-texture at the leaf of fine nuances.

Lastly, Gabor filters have been extensively used in plant leaf recognition but since it suffers form limitation on the maximum bandwidth and also the presence of the nonzero DC element in the even-symmetric filter. Gabor filters would not be the go-to option for research that seeks to achieve broad spectral details with maximal spatial localization. This limitations are addressed by Log-Gabor filters, therefore can be used to improve accuracy for plant identification.

In the future work, the approach can be fused with Convolution Neural Networks to exploit the advantages of deep learning techniques.

Author's Contributions

Stephen Opoku Oppong: Collected analyzed the papers for the review and drafted the manuscript.

Frimpong Twum: Verified and supervised the whole project.

James Ben Hayfron-Acquah and Yaw Marfo Missah: Reviewed the manuscript for significant intellectual content.

Ethics

The corresponding author confirms that all the other authors have read and approved the manuscript and no ethical issues involved.

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