



Development of PCAHOG Feature Extraction with ROTN-ELMSOM Classifier for *Aspergillus* Species Identification

by

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LIST OF ABBREVIATIONS

2D	Two-Dimensional
3D	Three-Dimensional
AM	Ante-Mortem
ANN	Artificial Neural Network
BMU	Best Matching Unit
CA	Classification Accuracy
CCV	Colour Coherence Vector
CT	Computed Tomography
dB	Decibels
DSF	Domain-Specific Features
ELM	Extreme Learning Machine
ELMSOM	Extreme Learning Machine and Self-Organizing Map
ROTN-ELMSOM	Robust Optimized Threshold Neural Network ELMSOM Model
FLICM	Fuzzy Local Information C-Means
FMM	Finite Mixture Model
GF	General Features
HMMD	Hue, Min, Max, Different
HOG	Histogram of Oriented Gradient
HSV	Hue, Saturation, Value
JPEG	Joint Photographic Experts Group
KKT	Karush-Kuhn-Tucker
KNN	K Nearest-Neighbour
LBP	Local Binary Pattern
LDA	Linear Discriminant Analysis
MLP	Multilayer Perceptron
MSE	Mean Squared Error
PC	Principal Component
PCA	Principal Component Analysis
PCAHO	Principal Component Analysis and Histogram of Oriented Gradient
PM	Post-Mortem
PRI	Probabilistic Rand Index
PSNR	Peak Signal-to-Noise-Ratio
RBF	Radial Basis Function

RGB	Red, Green, Blue
ROI	Region of Interest
RSF	Resource Selection Functions
SC	Spatial Constraints
SDA	Sabouraud Dextrose Agar
SIFT	Scale Invariant Feature Transform
SLFN	Single Hidden Layer Feedforward Neural Network
SMM	Student's t Mixture Model
SOM	Self-Organizing Map
SVFMM	Spatially Variant Finite Mixture Model
SVM	Support Vector Machine
VC	Vapnik Chervonenkis
YCbCr	Luminance and Chrominance

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Pembangunan Pengekstrakan Ciri PCAHOG dengan Pengelas ROTN-ELMSOM untuk Pengenalpastian Spesies *Aspergillus*

ABSTRAK

Aspergillus merupakan salah satu jenis kulat saprofit bawaan udara yang mampu hidup dalam pelbagai keadaan iklim dan menyebabkan pelbagai jenis penyakit. Kulat ini boleh memberi manfaat dan juga merbahaya kepada manusia dan haiwan. Pemeriksaan mikroskop langsung sering digunakan oleh ahli mikroskop sebagai alternatif untuk mengenal pasti spesimen yang disyaki terkena jangkitan kulat. Walau bagaimanapun, pengesanan terhadap identifikasi sering diperlukan kerana struktur *Aspergillus* yang kompleks dan berbeza-beza dalam setiap kitaran. Selain itu, kesilapan pengenalpastian boleh berlaku, terutamanya di antara spesies yang mempunyai ciri yang serupa. Bagi mengelakkan kesalahan dalam pengenalpastian dan keperluan identifikasi yang tepat, satu pendekatan pengecaman spesies *Aspergillus* berdasarkan komputer yang merangkumi peringkat pengenalan dan identifikasi telah dicadangkan. Proses pengecaman adalah peringkat penting untuk mengesan kehadiran kulat, oleh itu, kaedah segmentasi berasaskan kawasan aktif dicadangkan. Kaedah ini tidak bergantung sepenuhnya pada kecerunan atau pinggir tajam objek dan pelaksanaan fungsi set tahap untuk evolusi lengkung mampu mengurangkan kos komputasi dengan berkesan. Dua kaedah yang berbeza diuji dan dibandingkan, bertujuan untuk melihat keupayaan pendekatan untuk segmentasi 240 imej *Aspergillus* yang mempunyai empat spesies berbeza. Eksperimen yang dijalankan telah dibandingkan dengan teknik garis dasar dan kaedah yang dicadangkan telah mengatasi prestasi dari segi ketepatan dan spesifikasi, dengan purata 90% dan nilai PSNR lebih dari 40dB. Sementara itu, kaedah kontur aktif (*Snake*) berprestasi lebih baik dari segi sensitiviti dengan nilai melebihi 80% untuk kesemua spesies. Setelah itu, dalam peringkat klasifikasi, kaedah analisis komponen utama dan histogram berorientasikan kecerunan (PCAHOG) untuk mengekstrakan ciri bersama-sama dengan pengelasan mesin separuh bersupervisi pembelajaran melampau dan peta penyusunan sendiri bersama ambang yang optimum (ROTN-ELMSOM) telah digunakan. PCAHOG mengekstrak nilai kecerunan piksel untuk mengurangkan dimensi pangkalan data sambil mengekalkan titik data yang berniformasi. Representasi data yang dihasilkan kemudiannya digunakan dalam pengelasan ROTN-ELMSOM dan memanfaatkan kelebihan kedua-dua pengelasan yang tidak bersupervisi dan bersupervisi. Pendekatan SOM memudahkan pembelajaran struktur asas dengan itu, membolehkan pendekatan ELM menjalankan proses pengelasan. Walaubagaimanapun, untuk menangani isu pemasangan berlebihan disebabkan oleh data yang terhad, parameter ambang diperkenalkan di dalam lapisan tersembunyi. Penambahan ini meningkatkan prestasi klasifikasi dengan meminimumkan kemasukan neuron berlebihan. Selain itu, beberapa eksperimen lain dijalankan untuk menentukan nilai optimum untuk parameter seperti bilangan *epoch*, saiz jiran, bilangan neuron, nisbah latihan, dan peraturan berat untuk proses pengelasan ROTN-ELMSOM. Berbanding ELMSOM asal, ketepatan, sensitiviti, dan spesifikasi diperolehi kaedah ekstraksi ciri PCAHOG dan kaedah klasifikasi ROTN-ELMSOM adalah melebihi 96% dan ini telah mengesahkan keberkesanan kaedah yang dicadangkan.

Development of PCAHOG Feature Extraction with ROTN-ELMSOM Classifier for *Aspergillus* Species Identification

ABSTRACT

Aspergillus is one of the most ubiquitous of the airborne saprophytic fungi, capable of thriving in various climatic conditions and causing multiple types of illness. These fungi can be both beneficial and harmful to humans and animals. Direct microscopic is often used by microscopist as an alternative for identifying any specimens suspected of fungal infection. However, confirmation towards identification is often necessary due to the complex and dissimilar structure of *Aspergillus* in each cycle. In addition, misidentification can occur, especially among species with similar features. To prevent misidentification and the need of accurate identification, a computer-based *Aspergillus* species identification approach is proposed which encompassed recognition and identification stages. The recognition process the crucial stage to detect the presence of fungi therefore, an active region-based segmentation method is proposed. This method is not solely depending on the gradients or sharp edges of the object and implementing level set function for curve evolution which effectively reduced computational cost. Two different methods were tested and compared, aiming to observe the approaches' ability to segment different 240 of *Aspergillus* images representing four species. Experiments conducted have been compared with the baseline technique and the proposed method is outperformed in terms of accuracy and specificity with an average of 90% and PSNR value of greater than 40dB. Meanwhile the active contour (Snake) was slightly underperformed but well performed in terms of sensitivity with values exceeding 80% for all the species. Afterwards, moving on the classification stage, principal component analysis and histogram of gradient oriented (PCAHOG) features extraction methods are employed in conjunction with semi-supervised robust optimized threshold neural network extreme learning machine and self-organizing map model (ROTN-ELMSOM) classifiers. PCAHOG captured pixels gradient values to reduce the dimension of the database while retaining the valuable data points. The resulting compact data representation is subsequently utilized in ROTN-ELMSOM classification and capitalized on the advantages of both unsupervised and supervised classifier along with an adjustment in the hidden layer. The SOM approach facilitated learning the underlying structure thus, enabling ELM approach to execute the classification process. However, to address the overfitting due to limited data availability, a threshold parameter was introduced in the hidden layer. This addition enhanced the classification performance by minimizing the inclusion of redundant neurons. Furthermore, a few other experiments are conducted to determine optimum values for parameters such as number of epochs, neighbourhood size, number of neurons, training ratio and weight rule respectively for ROTN-ELMSOM classification process. Compared to original ELMSOM, the acquired accuracy, sensitivity and specificity that are greater than 96% substantiated the effectiveness of the proposed PCAHOG features extraction and ROTN-ELMSOM classification methods.

CHAPTER 1 : INTRODUCTION

1.1 Introduction

Fungi are living organisms which can be single celled or complex multicellular organisms with the ability to thrive in various environmental conditions (Márquez-Zacarías, Conlin, Tong, Pentz, & Ratclif, 2021) (Santiago, Goncalves, Gomez-Silva, Galetovic, & Rosa, 2019). The habitat not only on the ground but also below ground in the soil, in oceans and even within inland water environment (Santiago, Goncalves, Gomez-Silva, Galetovic, & Rosa, 2019) (Anthony, Bender, & van der Heijden, 2023). In addition, the fungi often can be found live on dead and rotting animal, human skin as well as airborne (Amato, et al., 2017). In the emerging of the bioeconomy era, fungi play a crucial role for both environment and human hence, the range of new uses of fungi need to spread out to raise global awareness on importance of fungi. On one hand, fungi activity has been exploited for beneficial purposes in various industries such as in food production, medicine, and agriculture. For example, *Penicillium* and *Aspergillus* are used in antibiotics production for medical industry and yeast is used to produce bread and drinks (Solomon, Tomii, & Dick, 2019). While on the other hands, fungi can be infectious to the living and this issue has increased at an alarming rate in the past few decades. Although most fungi are harmless, but it offers significant risk to those with weakened immunity.

The fungi infections can be acquired either by environmentally or endogenously. Some fungi grow in environment niches as saprophytes and patient can be infected via inhalation of spores easily. Meanwhile, the infection acquired by endogenously, the

infection is normally originated from the colonisation cells of the patient body's part (Lori & Callan, 2004) (Sprague, Kasper, & Hube, 2022). Despite thousand species of fungi existed, *Aspergillus* is one of the most ubiquitous of the airborne saprophytic fungi that can be found in various climatic conditions and could cause multiple type of illness from a simple allergic reactions to life-threatening disease (Mousavi, Hedayati, Hedayati, Ilkit, & Syedmousavi, 2016) (León-Buitimea, Garza-Cervantes, Gallegos-Alvarado, Osorio-Concepción, & Morones-Ramírez, 2021). *Aspergillus*'s conidia present in the air and constantly inhale by human but normally it harmless except for people with compromised immune system (Verburg, Neer, Duca, & Cock, 2022). *Aspergillus*' structure as shown in Figure 1.1 consists of a few informative and important parts such as phialides, conidia, vesicle and conidiophore/stipe which are useful for species recognition (Larone, 2002) (Garcia-Rubio, Oliveira, Rivera, & Trevijano Contador, 2020).

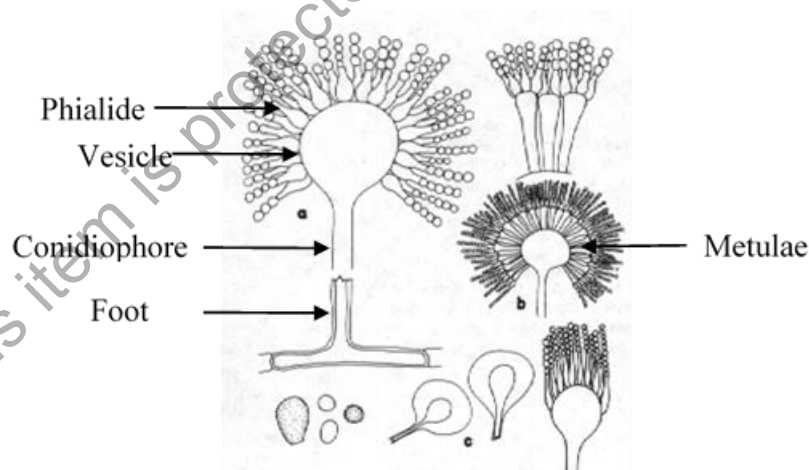


Figure 1.1 Structure of *Aspergillus*

The disease caused by *Aspergillus* is known as aspergillosis. Aspergillosis is rare in healthy people but significant among immunosuppressed patients. *Aspergillus* are allowed to invade, grow on the lungs and spread to all over the body. Moreover, the individuals with neutropenia, has a cancer or undergo chemotherapy or are on

corticosteroids also have high potential to be infected (Larone, 2002) (Earle, et al., 2023) (Oliveira, et al., 2023). *Aspergillus* has capability to infect different organs system but frequently, it will be found in human lungs and sinuses (Kanaujia, Singh, & Rudramurthy, 2023). As mentioned, the infection not limited to individuals with underlying health conditions but also could harm healthy people through direct physical contact or consumption of contaminated food. In terms of transmission through inhalation, existing studies does not provide conclusive evidence to assert that normal people could be easily infected.

The recognition of *Aspergillus* species is an important step in assisting the physicians with appropriate treatment decision. Commonly, the trained microscopist is responsible for handling specimens and conducting observation before providing relevant results. The specimens given will be observed microscopically in order to recognize the features and species of *Aspergillus*. Other than microscopic approach, macroscopic approach also can be used but normally this method is selected whenever the subject or object is visible with naked eyes and without magnifying instrument. Macroscopic is non-rapid process but during the examination, this approach could provide additional information about the fungi. This included details such as degree of growth, nature of surface growth and odour, presence of presence of turbidity and its nature (Okayo, Andika, Dida, K'Otuto, & Gichimu, 2020) (Suleiman, 2023). Even though these two methods are the most popular ones, the focus will primarily be on the microscopic approach.

The current method has some flaws so this study proposing fungi identification by using image processing to overcome the problems. The primary goal of this research

is to achieve the recognition of *Aspergillus sp.* through image segmentation followed by species identification through classification process. There are four species of *Aspergillus* which commonly found in Hospital Universiti Sains Malaysia (HUSM) included in this research such as *Aspergillus niger*, *Aspergillus flavus*, *Aspergillus fumigatus* and *Aspergillus terreus*. Several experiments have been conducted and the performances of the proposed method were evaluated to observe its applicability.

1.2 Problem Statement

1.2.1 Identification Process

The recognition of *Aspergillus* is crucial to study. The main purpose of *Aspergillus* recognition is to help the physician to identify the species of *Aspergillus* before running some specific clinical diagnosis to the patients. There are two ways that usually used to observe the characteristic of *Aspergillus*; colony/macroscopic and microscopic morphological. Microscopic morphological is usually to observe the physical features of *Aspergillus* while colony morphological is to observe the colour of the colony as different species has different colour of colony (Larone, 2002). Usually, direct microscopic is used by trained microscopist as one of the alternatives in identification process (Mäder, et al., 2015). Any specimen that suspected of having fungal infection will be hand over to be examined microscopically. However, even though this method offers a low costing, rapid availability of results and the equipment are accessible, it still rendering some flaws (Mathison & Pritt, 2017) and confirmation is often necessary.

Due to the aforementioned problems, computer method (image recognition/processing field) is proposed in this study as nowadays, image processing is one of the rapidly growing technologies. This method is proposed to enhance the effectiveness of testing, addressing existing issues and reducing errors. However, over the past decade, the identification of *Aspergillus* species in the field of image recognition has remained challenging. Several major processes such as data acquisition, pre-processing and classification are included in image processing. Image pre-processing which involves image segmentation is a process to distinguish the region of interest (ROI) with its background and a crucial step to recognize the structure of *Aspergillus* (Sonka, Hlavac, & Boyle, 2008). It involves dividing an image into relevant objects that can be further analysed in various ways. Selecting the right segmentation approach is highly significant for microscopic *Aspergillus sp.* image analysis. However, this remains a challenging task due to the lack of a standard segmentation approach used for *Aspergillus sp.* image, and also because of the biological objects which are highly variable.

The implementation of this method was motivated by limitations in the collected data. Although the original image has an informative structure of *Aspergillus* species, the images' quality can undergo changes over the time. The glass slides of specimen are the best to capture at an early stage of maturity, as the maturity of *Aspergillus sp.* evolves over time resulting in varying structures during the cycle. In early stage, the structure of *Aspergillus* is distinctive and easily observable while on aging slides, the structure has become more complex and challenging to recognize. The images obtained from the slides may not consistently on the top of quality and the structure of *Aspergillus* itself can be vary in each slide. For example, as the *Aspergillus* starts to mature, it releases conidia and the structure will be differ from the previous cycle. In this study, the focus will be