



Faculty of Cognitive Sciences and Human Development

**DESIGN AND DEVELOPMENT OF A SCENE RECOGNITION SYSTEM
USING NEURAL NETWORK MODELS**

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(Cognitive Science)
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**DESIGN AND DEVELOPMENT OF A SCENE RECOGNITION SYSTEM USING
NEURAL NETWORK MODELS**

ONG HUI XIN

This project is submitted
in partial fulfilment of the requirements for a
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ABSTRACT

Scene recognition has become one of the challenging aspects in machine learning. Not only that the performance of a state-of-art scene recognition system is bad, but it also requires a powerful computational device in order to carry out tasks. Hence, the central objective of this research is to design a new scene recognition system that performs well, at the same time reduce computational load of a scene recognition system. The biggest modification of the new scene recognition system is that it extracts objects as attributes for a classifier to perform scene classification. It also combines an object detection Convolutional Neural Network (CNN) model and a classifier. The method is simple, as it uses low computational power but also makes the scene recognition system perform well. There are two experiments done in this research to illustrate the performance of the new scene recognition system and the results are analysed. From the experiments done to classify different scene classes, it shows good performances of 97.11% and 80.22% of accuracy in classifying two distinct scene classes and three similar scene classes respectively.

Keywords: scene recognition, feature extraction, object detection, classification, deep learning, convolutional neural network

ABSTRAK

Pengecaman pemandangan telah menjadi salah satu aspek yang mencabar dalam pembelajaran mesin. Bukan sahaja prestasi sistem pengecaman pemandangan terkini tidak memuaskan, tetapi sistem ini juga memerlukan peranti komputasi yang kuat untuk melaksanakan tugas. Oleh itu, objektif utama penyelidikan ini adalah untuk merancang satu sistem pengecaman pemandangan baru yang berprestasi baik, pada masa yang sama mengurangkan beban komputasi sistem pengecaman pemandangan ini. Pengubahsuaian yang terbesar dalam system pengecaman pemandangan baru ini adalah system ini dapat mengekstrak objek sebagai atribut untuk digunakan oleh pengklasifikasi ketika melakukan klasifikasi pemandangan. System ini juga menggabungkan penggunaan model Rangkaian Neural Konvolusional pengesanan objek dan pengelasan. Kaedahnya mudah dengan menggunakan daya komputasi yang rendah tetapi juga menyebabkan sistem pengecaman pemandangan ini berfungsi baik. Terdapat dua buah eksperimen yang dijalankan dalam penyelidikan ini untuk menggambarkan prestasi sistem pengecaman pemandangan baru ini dan hasilnya telah dianalisis. Dari eksperimen yang dijalankan untuk mengklasifikasikan kelas pemandangan yang berbeza, sistem pengecaman pemandangan baru ini menunjukkan prestasi yang baik iaitu dengan ketepatan 97.11% dan 80.22% dalam mengklasifikasikan dua kelas pemandangan yang berbeza dan tiga kelas pemandangan yang serupa masing-masing.

Kata kunci: pengecaman pemandangan, pengekstrakan ciri, pengesanan objek, klasifikasi, pembelajaran mendalam, Rangkaian Neural Konvolusional

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Say you are given a text by a recent state-of-the-art visual recognition system on what it sees, the text might sound like this: “There are many tables and chairs lined up in a hall. People are sitting on the chairs facing down at their tables. There are stationeries on the tables,” what would you imagine in your mind what place is it in the image that the system sees? You would think that the image it sees is in a classroom. However, it may be in an exam hall, or a huge library.

To a visual recognition system, its final goal may be recognizing what objects there are in an image. Nevertheless, recognizing the scene of an image is also very important as it makes the context for object recognition reachable (Zhou et al., 2014). Scene recognition is one kind of visual classification (Li et al.; Ponce et al. as cited in Mao et al., 2019). In fact, it determines the context of an image by interpreting the objects in it (Mao et al., 2019). It allows more meaningful information to be told in object recognition (Zhou et al., 2018). For example, a table in a kitchen is used to eat or prepare foods, while a table in an office is used to support a computer and stationeries. Scene recognition is needed in many areas like remote sensing, aerial scene classification, computer vision and robotics (Mao et al., 2019). For example, in Zhou et al.’s study (as cited in Mao et al., 2019), a method is proposed to recognize under-construction-building areas when scenarios are complex.

Talking about scene recognition, it is always related to pattern recognition. Based on Theodoridis and Koutroumbas (2003), pattern recognition is defined as a scientific discipline whose purpose is to classify objects into many of categories or classes. In other words, its major goal is classification, either supervised or unsupervised. The elements which are crucial to be taken care of in a pattern recognition system are the definition of each pattern class, sensing

environment, feature extraction, learning rate of the system, choosing of training and testing sets of data and evaluation of system performance (Jain, Duin & Mao, 2000). Pattern recognition is a necessary part in most of the intelligent systems built for decision making purpose (Theodoridis & Koutroumbas, 2003).

There are a lot of pattern recognition frameworks introduced in today's world. In statistical machine learning, the most important aspect is the selection of desired features from the input instances to solve a particular problem. In the case where the input space does not fit the desired output, one of the ways to solve it is to take an intermediate feature space so the instances can be mapped into it. To define the intermediate feature space, one can either explicitly hand-code the features in it, implicitly design a kernel function, or allow automatic learning in the computer system. The first two methods cost tremendously in terms of duration of computation or expert knowledge, especially when it comes to dealing with high dimensional input spaces like images as input instances (Arnold et al., 2011).

The third method which is to make the machine learn automatically, is indeed saving human energy and expertise. This is because machine learning makes learning process in machines occur automatically, without the machines been explicitly programmed (Wuest et al., 2016). In fact, machine learning application is exponentially increased since the last two decades due to many reasons. One of the factors as mentioned by Smola and Vishwanathan (2008) is that the amount of data available in the world is increasing, allowing more smart data analysis to be done. Hence, with the data as input instances, machines can learn more effectively and accurately. Another reason that machine learning kept developing is that the usability and power of machine learning tools available are increasing, making more advanced machine learning algorithms been discovered (Larose, 2005).

Nevertheless, when dealing with highly nonlinear functions, the machine learning structures are represented with much more compact neural network in terms of parameters'

number within it, with deeper architectures as compared to the shallow ones (Arnold et al., 2011). This technique of using deep architectures as mentioned is called deep learning (Schmidhuber, 2014). In the case when images are set as input instances, convolutional neural network (CNN) is applied. In fact, CNN's performance in image classification is the current state-of-the-art (Sultana, Sufian & Dutta, 2018). Hence by using CNN, deep features can be learned for scene recognition tasks.

1.2 Problem statement

In machine learning, pattern recognition represents the classification of different kinds of output values depending on their respective input values, based on a specific pattern recognition algorithm (Rao & Reddy, 2011). There are a lot of pattern recognition frameworks introduced in today's world. Among them, the statistical approach in machine learning is the most intensively studied and practised techniques (Jain, Duin & Mao, 2000). Statistical pattern recognition technique is a classical method applied in pattern recognition (Rao & Reddy, 2011). In traditional statistical machine learning, every pattern is classified based on its features or measurements. How well a pattern is recognized depends on how useful and specific the features extracted from the particular class of pattern as compared to other classes (Jain, Duin & Mao, 2000). This classical method of classification deals with statistics and probability of features towards a class of pattern, but not the relationships between the features those a class of pattern has (Rao & Reddy, 2011).

As the classical technique of pattern recognition depends on feature recognition, it involves a lot of image pre-processing like image segmentation and enhancement (Balan & Sunny, 2018). When using the same classical technique in object recognition, features are also needed to be recognized to identify an object, for example two eyes sitting above a mouth indicates a face (Zhou et al., 2018). Hence, when dealing with scene recognition, a lot more

features would need to be recognized in order to identify a scene. In this case it is very time consuming and computational expensive.

Besides, shifting from the classical techniques to deep learning method, deep neural networks has its requirements too. In deep learning neural network models, image data are collected and input as a whole to train the model (Sultana, Sufian & Dutta, 2018). This technique is the same for both object and scene recognitions, hence plenty of image data is needed in deep learning neural network models. In fact, with huge dataset, the Squeeze-and-Excitation Network (SENet) achieved the lowest error rate of 2.251% in object recognition in ILSVRC 2017 classification challenge (Hu, Shen & Sun, 2018).

Furthermore, whereas the enormous recent research in object recognition tasks keeps developing because of the large datasets available like ImageNet and the advancements made in CNN especially for high level feature learning, performance shown in scene recognition has not achieved the same success level (Zhou et al., 2014). One of the factors is that appearance of real-world scenes in different places around the world differs (Zeng et al., 2018). Besides, in indoor scene recognition, images of different categories have similarities, like offices and machine rooms, as well as images within similar categories have differences. Apart from that, label classification of scenes has huge subjectivity (Guo et al., 2018).

Therefore, in this study, various scene recognition algorithms are studied and understood in depth. Then, the algorithms are experimented and evaluated using a well-known tool. Besides, image pre-processing based on saliency detection technique is explored to improve the accuracy of a scene recognition system. Similar research in the past shows positive results, that saliency detection technique applied before image data training help improving the accuracy of a CNN model. One example is the research done by Hussain, Rao and Masthani (2016) in object recognition, where saliency detection technique helped reduce the number of regions detected in an image, thus successfully avoided false regions in the image. Besides, in

Lopez-Alanis et al.'s study (2019) using visual saliency detection technique in object recognition, it is proven that the method leads to more stable and better results.

1.3 Objectives

Generally, this study aims to conduct experimental studies by implementing deep learning algorithms in scene recognition and evaluating its performance by using a well-known evaluation method. The objective of the study is further divided into the below categories:

- To study in depth the deep learning algorithms for scene recognition.
- To implement feature extraction using Convolutional Neural Network (CNN).
- To design and develop a new scene recognition system based on neural network models.
- To evaluate the performance of the system by using a well-known evaluation method.

1.4 Scope of Study

The study focuses on exploring various recent scene recognition algorithms, to study in depth on them. Objects as features are extracted using a Convolutional Neural Network (CNN) model to be fit into a classifier to carry out scene classification. Experiments are carried out to test the algorithms and evaluate them with a well-known tool. The goal is to reduce the computational load of training model, to hopefully also achieve a higher accuracy testing result.

The database that will be utilised is the Google image database, as it is rich and easy to be reached. However, the constraint of using this database is that it is a huge database and contains a lot of noisy, irrelevant data that acts as “noise”. Hence, the solution to this constraint is to filter out the “noise” before use. The method of acquiring database for my system is that three scenes that are common are selectively chosen from the Google database to be utilised.

CHAPTER TWO

LITERATURE REVIEW

2.1 Image pattern recognition and computer vision

An image is considered as the most important type of pattern we see every day. There are plenty of things displayed in images to us, especially biometric patterns like faces, fingerprints, palmprints and iris. Therefore, image pattern recognition strives to explore how a pattern can be recognized in an image. Generally, an image pattern recognition system is made of four parts, which are a camera that take photos of images, an image pre-processor that enhance the images so that desired characteristics of the images are significant, a feature extraction model that aims to obtain distinct features from images, and a classification model that classifies the image samples into desired classes based on the features extracted (Yang & Yang, 2009). The process aims to make description, grouping, and classification of different patterns where a pattern is defined as an entity that matches a name. Pattern recognition problems in the real-world are very diverging and critical as they aid in most of the human decision-making processes (Chen et al., 2001).

Although an image pattern recognition system can hardly perform as good as a human being, it is used in various applications in today's world. For instance, the optical character recognition (OCR) takes a single character image and classify it into one of the 52 classes, which includes the list of all alphabetical letters, in both lower and upper cases. Researchers also actively pay attention to the recognition of faces and different kinds of objects like chairs and cars. (Uchida, 2013).

Like any other kinds of classification methods, information availability is important to decide the scheme of an image pattern recognition model, for it can be in the supervised or unsupervised schemes. Based on the knowledge of some predefined classes, a supervised scheme assigns one class to an unknown pattern to be a member of that class. On the other

hand, an unsupervised scheme divides input patterns into different clusters called classes. (Chen et al., 2001).

In fact, image recognition plays a big role in computer vision. Associating with modern computer technology, the neural network image recognition technology keeps improving (Li, 2015). In image recognition development, knowledge in different fields like image processing, pattern recognition and artificial intelligence (AI) is necessary and important (Hinton et al., 2012). In order to conduct image recognition, first, corresponding images must be got by image acquisition device and then transform into digital images. Then through image recognition, its various information can be obtained (Li, 2015).

As mentioned, machine vision is a field in which pattern recognition is at importance (Theodoridis & Koutroumbas, 2003). Whilst, computer vision allows perception of machine vision. It allows developing computer intelligent systems to acquire possible information from an image (Lugli & Melo, 2017). It develops techniques that help in computers' comprehension on the content of a digital image like a photograph or a video (Brownlee, 2019). In fact, the subjects that matters to computer vision is very broad. Topics for instance image formation, image processing, segmentation, stitching, three-dimensional (3D) shapes, image-based rendering and recognition are all closely related to the term "computer vision" (Szeliski, 2011). Vision is widely agreed as the process of discovering what and where the world is presented from images (Marr, 1982).

2.2 Object recognition

Object recognition is the labelling of objects in images based on priori, a set of known object models. Human beings can perform this task effortlessly and instantaneously. In contrast, it is found surprisingly difficult to perform the same task if human beings are replaced by object recognition systems. The task's algorithmic description to be implemented on those systems

has been completely hard. Precisely, when an object recognition system is provided an image that contains object(s) of interest as well as a set of object labels, it should be able to determine the right labels of objects and the regions they seat correspondingly in the image. Hence, object recognition problems are corelated to segmentation problems. Segmentation is impossible if there is not even partial object recognition and vice versa (Jain, Kasturi & Schunck, 1995).

In recent years, research on object detection has surged as it is important in image understanding and video analysis. Traditional methods of detection of object utilise features that are handcrafted and shallow architectures which are capable to be trained. Their performance become stagnant easily by combining multiple image features that are low level with context of high level obtained from object detectors as well as scene classifiers. As deep learning development keeps improving, the tools available are becoming powerful too, for example tools that can learn semantic. The difficulties raised by traditional architectures can be solved with the introduction of high-level and deeper features into the model. Different models have different designs of network architecture, and so to have different training strategy and optimization function (Zhao et al., 2019).

2.3 Scene recognition

Over the past decades, researchers in computer vision have been extensively studying scene recognition and proposing a number of different scene recognition methods (Luo & Boutell, 2005; Cao & Fei-fei, 2007; Wu et al., 2015). Scene recognition mainly functions as an identifier to indicate where an image is at with the objects, for example the office, beach and road. Although without applying the place category, a system may still recognize different scenes by having a more comprehensive list of objects in an image and details on their spatial connections, a place category is still important to give suitable levels of abstraction so that a long and complicated description can be prevented. Similarly to objects, a place owns functions

and properties. A place is made of parts and for some parts, there are names for them to be compared to their corresponding objects (Zhou et al., 2018). For example, a human object can be composed into parts like hands, legs, face, etc., while a café scene can be composed into humans, tables, chairs, cups and plates, etc.

In a real scene recognition system, representation and classification of scenes are the major stages. The purpose of scene representation is to extricate distinct features so that different scene images can be differentiated easily, whereas the scene classification stage builds useful classifiers to make different scene categories discernible. The two stages have different degree of effects towards a scene recognition system's performance, where scene representation creates a more obvious influence as it seeks for both generalized properties in a scene category and different properties in between different scene categories. However, the spatial layouts of scenes usually would also show properties over different scene categories and objects within the same scene not only covers a broad variety, but they more often than not also exist in other different scenes. Therefore particularly, those properties are hard to be captured. Subsequently, the main and tough challenge remains as how more distinct representations can be extracted to make inter-class scene categories more differentiated and the variation of intra-class scene categories to be minimized (Cheng et al., 2018).

2.4 Artificial neural network (ANN)

The artificial neural network (ANN) technology imitates human brains in their tasks of input signals handling as well as the conversion of input signals into output signals (Wesolowski & Suchacz, 2012). The ANN model is an effective algorithm as it considers non-linearity in across features and output signals. ANN models are non-parametric, where underlying functions would not be known by researchers when complicated phenomenon is

dealt with. As so, without explicitly defined function assumptions, ANN can still learn from the input data (Zhang, 2016).

2.4.1 Biological neuron

Human brains process information through parallel operations of biological processing components, to produce correct functional processes like thinking and learning. The central nervous system has basic cells called neurons. A neuron conducts electrical stimuli triggered by physical-chemical reactions in some particular conditions, called impulses. A neuron consists of three major elements, called dendrites, cell body or soma, and axon (See *Figure 1*).

Dendrites build up the dendritic tree by having a few thin extensions. The dendrites of sensory neurons receive stimuli from the external environments because they have direct contact to the environments. Whilst, the others have their dendrites receiving stimuli from other neurons. The cell body then processes information that is received by the dendrites, so that an activation potential can be produced to indicate if an electrical impulse can be triggered along its axon. Major cytoplasmic organelles such as nucleus and mitochondria are also found in cell bodies (Silva et al., 2017). Next, the processed information by a cell body would be passed to the axon, which is a single extension that helps to transmit the triggered electrical stimuli to the dendrites of other connecting neurons, through axon terminations called synaptic terminals.

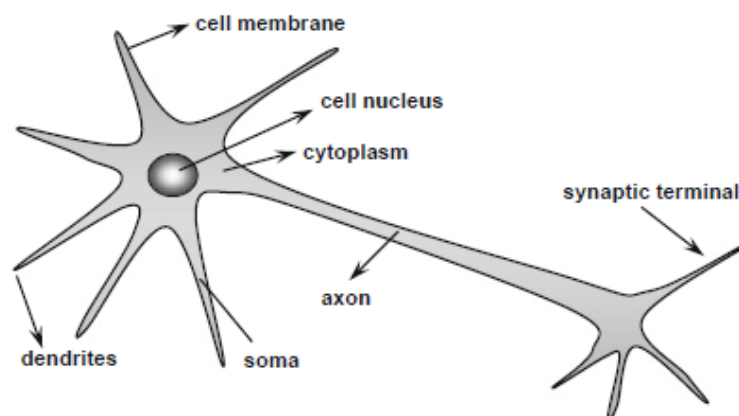


Figure 1. Biological neuron. Reprinted from *Artificial neural networks: A practical course* (p. 9), by I. N. Silva et al., 2017, Cham: Springer International Publishing. Copyright 2017 by Springer International Publishing Switzerland. Reprinted with permission.

The synapse is the space that connects two or more neurons and enables the transfer of neurotransmitters from neuron's synaptic terminal to another neuron's dendrites, as shown in *Figure 2*. It can be observed that no physical contacts exist between neurons in the synapse. Therefore, the neurotransmitters released on the synapse play a role as to weight the transmission. A neuron's function depends on its synaptic weighting that is dynamic, as it depends on its cerebral chemistry too (Hodkin & Huxley, as cited in Silva et al., 2017).

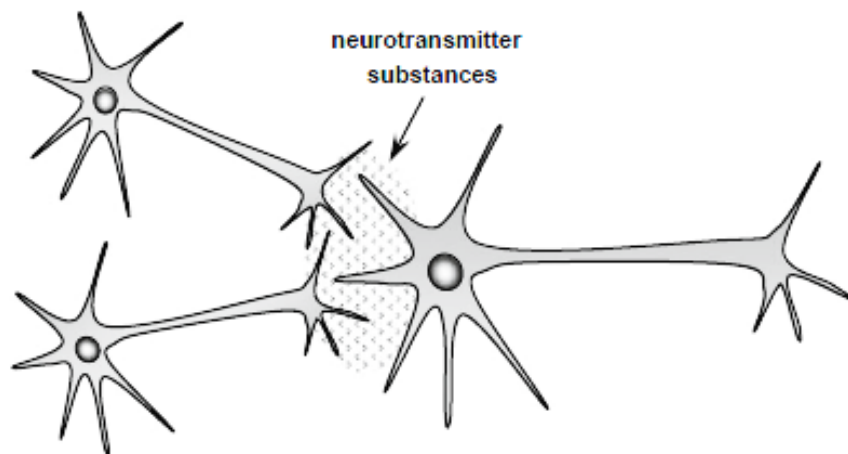


Figure 2. Illustration of the synaptic connection between neurons. Reprinted from *Artificial neural networks: A practical course* (p. 10), by I. N. Silva et al., 2017, Cham: Springer International Publishing. Copyright 2017 by Springer International Publishing Switzerland. Reprinted with permission.

In a nutshell, although biological neurons might in the beginning appear to perform extremely simple tasks, they work together to make a human brain works, for example processes which are carried out and handled by the brain. A biological neural network, featured by so many unpredictable properties, is predicted to have approximately 100 billion (10¹¹) neurons, and every neuron is interconnected to a mean number of 6,000 other neurons through synapses. Therefore, a biological neural network is predicted to have a sum of 600 trillion synapses (Shepherd, as cited in Silva et al., 2017).

2.4.2 Artificial neuron

The development of the structure of an artificial neural network (ANN) was inspired by human nervous systems. Artificial neurons that act as the computational components or

processing units in an ANN are similar to a simplified version of a biological neural network model (Hodgkin & Huxley, as cited in Silva et al., 2017).

The artificial neurons in ANNs are nonlinear. They keep generating outputs as well as performing tasks like gathering input signals, rearranging the signals based on their corresponding operational responsibilities, and generating responses through the activation functions set to them. McCulloch and Pitts had proposed the simplest artificial neuron model which incorporates the parallelism and high connectivity of a biological neural network, and it is still most implemented in various ANN structures (Silva et al., 2017).

Using that model, each neuron in an ANN is applied as shown in *Figure 3*. The set of input signals $\{x_1, x_2, \dots, x_n\}$ illustrates the multiple input nodes that go into an ANN, similar to how dendrites of biological neurons receive electrical impulses. On the other hand, a set of synaptic weights $\{w_1, w_2, \dots, w_n\}$ is used to imitate weighting processes conducted by the synapse of a biological neural network are applied in an ANN. With the external information of input signals and internal-decided synaptic weights, the model weight every input signal $\{x_i\}$ by multiplying each of them with its relative synaptic weight $\{w_i\}$. Thus, the output of the model, denoted by u , is simply defined as the summation of all weighted input signals (Silva et al., 2017).

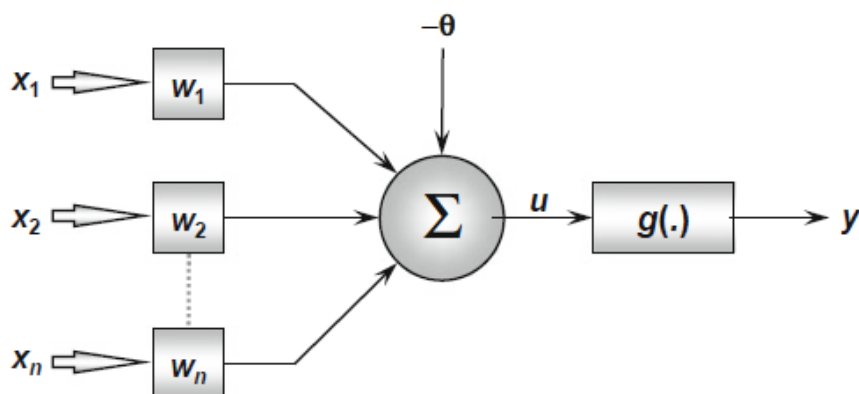


Figure 3. The artificial neuron. Reprinted from *Artificial neural networks: A practical course* (p. 12), by I. N. Silva et al., 2017, Cham: Springer International Publishing. Copyright 2017 by Springer International Publishing Switzerland. Reprinted with permission.

Considering *Figure 3*, there are seven fundamental elements to build an artificial neuron: