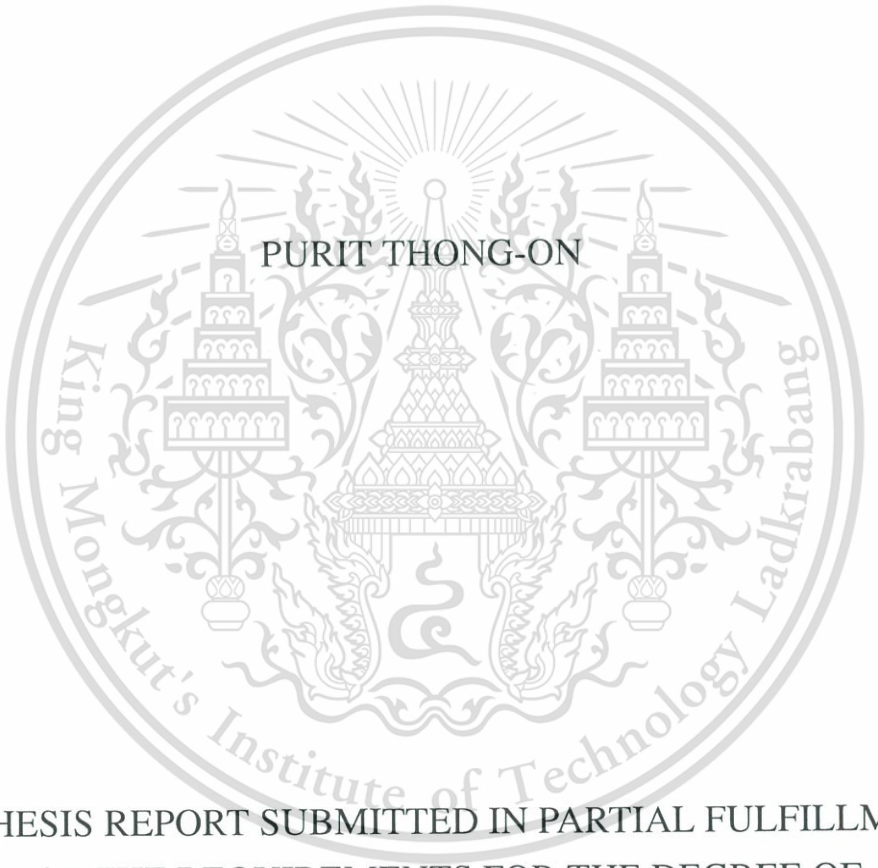
DETECTION OF LIVER FIBROSIS USING TRANSFER LEARNING BASED MULTI-OBJECTIVE GENETIC PROGRAMMING

PURIT THONG-ON



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THESIS TITLE	Detection of Liver Fibrosis Using Transfer Learning Based Multi-Objective Genetic Programming
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ABSTRACT

The liver is an essential organ of human body. It's responsible for detoxification and production of many biochemicals. It also maintain the storage of many substances such as vitamins and glucose.

Liver fibrosis is one of the main causes of liver diseases. It is an elastic tissue which replaced the normal tissue during the scarring process when the liver is damaged. The accumulated amount of fibrosis resulted in the liver organ being distorted and malfunctioned. This leads to many other diseases such as liver currhosis or liver cancer. Many researchers tried to applied image analysis approach to automatically determine the amount of fibrosis in the liver which require feature selection and extraction for separating liver fibrosis tissue pixels from normal tissue pixels.

In this research, the automatic approach for construction of feature extractor was applied to create an image analysis system that quantify the amount of liver fibrosis tissue in liver biopsy images using a variant of evolutionary computation algorithm called multi-objective genetic programming (MOGP). The MOGP is an algorithm designed for search and optimization of programs. Furthermore, transfer learning schemes also implemented together in order to support the process.

To validate our approach, the proposed method was first compared with a benchmark approach which applied image analysis method with manual feature selection by human. The experiments are conducted and statistical measurements are calculated. The results showed that the proposed method outperform the benchmark approach in terms of fibrosis detection.

In addition, normal MOGP approach which is our previous published work was also used to compare with the proposed method to test the performance with and without transfer learning method implemented. The experiment results displays the advantage of the proposed method

which achieve statistically better performance in terms of fibrosis detection. Therefore, the transfer learning mechanism did improve the program optimization process.

ACKNOWLEDGEMENTS

This research requires a lot of knowledge and studies which consume resources. The methods, tools, and workspace for this work implementation were supported by many individuals. This chapter is dedicated to extends gratitude toward them.

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CHAPTER 1

INTRODUCTION

This chapter presents the big picture of this research. First, we addresses the domain problems and explores related works in Sec:MotivationAndProblemDescription The scope of our research and the proposed method are explained in Sec:ObjectiveAndScope.

1.1 Motivation and Problem Description

The liver is an essential part in human body and living conditions. It perform various tasks such as producing or extracting important chemical substance. Fatty Liver, Liver Fibrosis or any other diseases and sickness which cause malfunction to the live might induce danger to human body and living conditions. Many diseases might not be detected until earlier stages which cause severe drop in survival chance. Therefore, earlier detection of any danger to the liver would contribute to prevention of patient health's from deteriorating and death.

The task for detecting anomaly in the liver can be achieved by the help of medical imaging device such as microscope, CT Scanner, MRI Scan, or ultrasound. The primary disadvantage of doing so is the information obtained contains loads of information which is difficult to discern between relevant and irrelevant information. Therefore, several researchers developed image analysis method to solve this kind of problem.Ribeiro et al. developed a diagnosis system with computing intelligence to classify liver steatosis in ultrasound images[33]. Similarly, Vicas and Nedevschi also utilized ultrasound simulation program for liver fibrosis detection [40]. Huang and Lai used support-vector machines to create a segmentation method for detection of nuclei cells location in liver biopsy

images [22]. Gordan et al. researched about using Bayesian technique for liver fibrosis image segmentation in liver biopsy images [21]. Kayaalti et al. achieved positive results for the usage of texture properties in liver CT images to diagnose the fibrosis stage [23]. Masseroli et al. develop an automatic image analysis system to determine the quantity of liver fibrosis [29]. Lin et al. presents the advantage and reliability of using color information for segmentation of liver fibrosis areas [28]. Meejaroen et al. applied Bayesian classifier to detect and quantify fibrosis areas in liver biopsy images [30]. Sumitpaibul et al. proposed an algorithm for liver fat detection in liver biopsy images [38]

The methods mentioned require expert knowledge and medical tools in order to achieve results. In addition, when using image analysis, the study of domain problems might take some time which can not be estimated in most cases. Therefore, experts knowledge are required. The methods also induce higher change of human error.

Recently, evolutionary computation (EC) has been applied in image analysis task. In particular reviews, automatic approaches to construction of feature extractor program have appeared to be very promising alternatives [3, 5, 15]. The approaches have domain independent characteristic and do not require knowledge from human experts to accomplish the task.

Krawiec and Bhanu uses cooperative coevolution linear genetic programming that encodes the simple operations to handle feature extractor construction for high complexity classification task [5]. Al-sahaf, Neshatian, and Zhang proposed a genetic programming based approach to construct a classification program where an individual program can perform input filtering, feature extraction, and classification [3]. Nagao and Masunaga applied Genetic Algorithm to perform image feature construction from primitive image processing operations[31]. Lin and Bhanu create a composite operators from various image processing operators using genetic programming [27]. Song and Ciesielski implements an automatic texture classifiers construction method using GP which classify and segment texture from bitmap image[36]. Trujillo and Olague discover various image processing operators for interest points detection in an image by applying GP-based approach. Watchareeruetai and Phanjan applied linear genetic programming to evolve a contour that can recognize leaf shapes [42]. Watchareeruetai et al proposed a redundancy regulator called canonical transformation that can speed up the evolution process of multi-objective genetic programming (MOGP) for automatic construction of feature extractor [15]. Shao et al. create feature descriptors by using MOGP to

combine several 2D image processing operations together [34]. Suganuma and Nagao develop feature construction method by applying image operation and transformation with multi-layered architecture [37]. Lilywhite et al. applied EA in object recognition tasks [26].

Furthermore, recent researches also apply transfer learning mechanisms which in many cases, help improve the results of their experiments. Transfer learning is a very interesting topic which can be implemented in many forms and architectures. However, the key concept of transfer learning is the use of existing knowledge and information and the method to pass them down. In most cases, the knowledge transfer often occurs when we need to solve multiple problems with similar nature or if not, requires a part of the previous knowledge. Currently, there were not many research on applying transfer learning in EC.

Haslam, Xue, and Zhang investigate the potential of genetic programming which implemented transfer learning and experimented on symbolic regression problem [45]. Iqbal, Zhange, and Xue proposed a transfer learning technique which improves the results on image classification problems [46]. Afterward, they also studies further on the cross-domain reuse of knowledge for genetic programming in complex image classification problems [48]. Kelly and Heywood found that reusing codes in genetic programming that solved a strategy game can also be used to improve the evolutionary process for solving another one which differ in complexity [47].

As a result, an automatic approach to feature construction using EC would be a potential solution to determine the amount of liver fibrosis. The process require less expert involvement and is autonomous. The obtained results can also be interpreted later on after this work. The application of transfer learning can also improve the result of evolutionary process along the way.

1.2 Previous Work on Automatic Construction of Feature Extractor

The previous work were about using evolutionary computation to construct feature extractor for liver fibrosis problems ([44]). The automatic approach proposed outperformed the manual approach by Meejaroen et al. [30]) in terms of fibrosis detection.

In this current work, we aims to improve the process by injection of transfer learning mechanism

which will be explained in later chapter.

1.3 Objective and Scope of Work

1.3.1 Objective

The purpose of this studies is to develop a liver fibrosis detection system which quantify the amount of liver fibrosis in liver biopsy images. The main focus is to apply multi-objective genetic programming to automatically construct an effective feature extraction program which is a component of the liver fibrosis detection system. In this research, transfer learning scheme was applied in order to help boost the process.

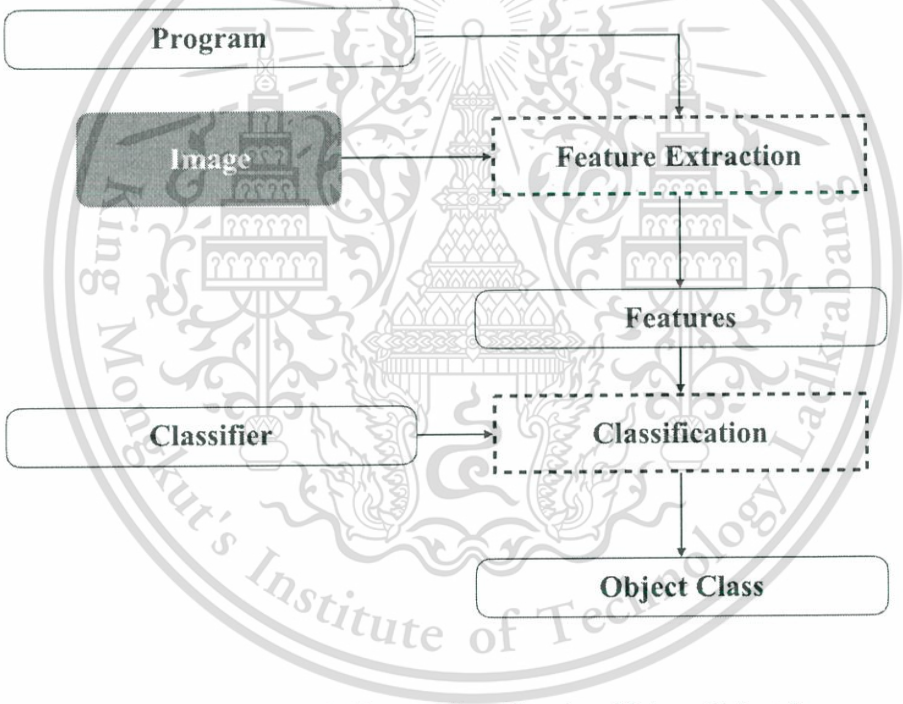


Figure 1.1: The Illustration of Object Classification Using Object Image as Input

1.3.2 Scope

The scope of this project are as follows:

- The input images must contains a single interest object in which its class is within the domain of interested object class.

- The domain of the object class must be specified.
- The system must be able to automatically extract the features from the image data without the knowledge of the user. However, a decent amount of training data must be given.
- MOGP is used to construct both segmentation program and feature extractor.
- A transfer learning method is applied and tested if this mechanism can increase the efficiency of feature extractor construction process.

The rest of the thesis is organized as follow. Chapter 2 provides necessary background knowledge to the rest of the thesis. Chapter 3 explains the methodology to image segmentation and feature extraction. Chapter 4 Explain the experiments in details. Chapter 5 Discuss and conclude the experiment result.

CHAPTER 2

BACKGROUND KNOWLEDGE

This chapter provides basic knowledge so that the activities and discussions in the sub-sequence chapter becomes more understandable. It provides a basic knowledge in the mechanisms behind the system such as the evolutionary algorithm, and image processing operations

2.1 Evolutionary Algorithm

Evolutionary algorithm (EA) is a mechanism with the propose of solving optimization problems. This algorithm embodies the concept of natural selection by Charls Darwin. It mimics the phenomena where organisms in an environment (limited resource) evolve itself so that each one becomes better at survivability. Along the way, some species might slowly disappear due to low adaptability and cannot win the race with other species to gain its own resources.

The said concept is implemented in EA. In this case, it abstracts the objective problem as an environment while organisms are population of individual solutions that designed to solve the problem. However, each individual has its own capability to optimize the problem so the fitness value visualizes the capability of each problem into numbers by some type of calculation.

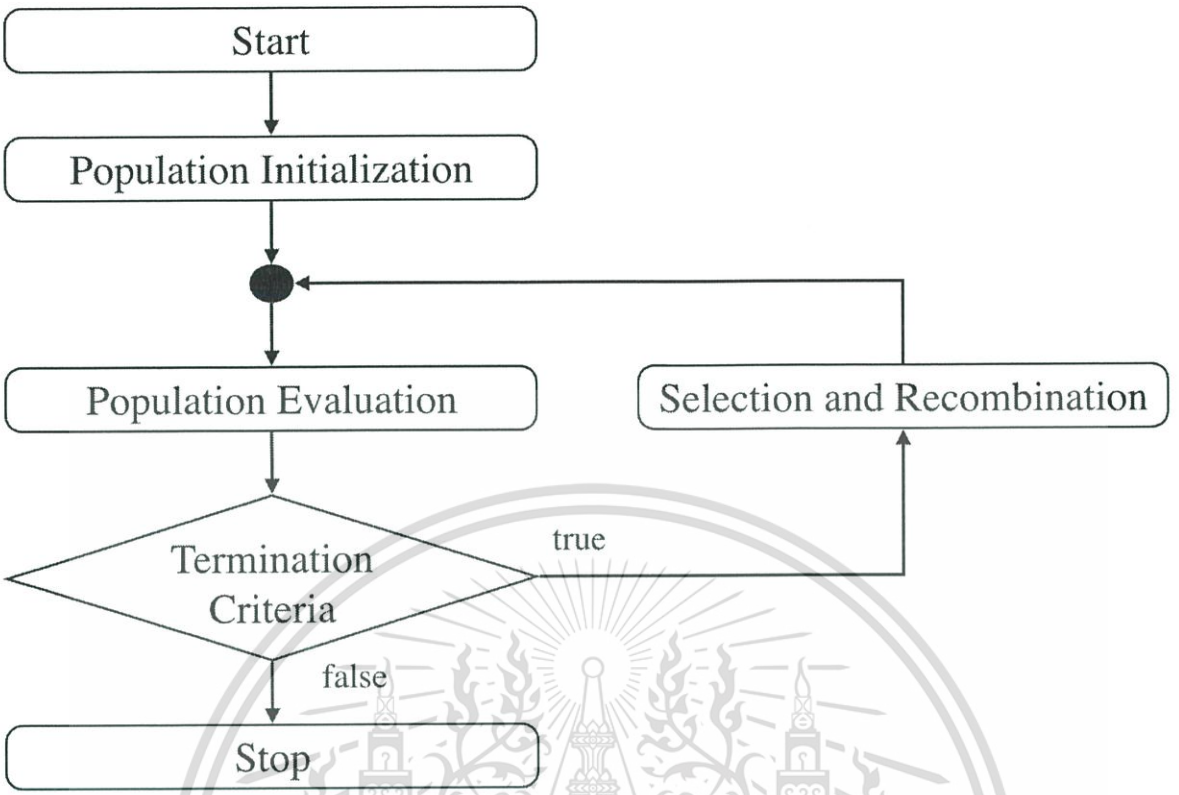


Figure 2.1: Evolutionary Algorithm Flowchart

The flowchart in Fig:EAFlowchart depicts the iterative execution of the algorithm.

1. *Population Initialization*: use some method (maybe random) to generate a population consists of individuals.

2. *Population Evaluation*: evaluate every individual with some method to quantize its problem solving capability into fitness value.

3. *Termination Criteria*: check if the termination condition is met for example, the number of iterations or if there exist an individual which has fitness value above a certain threshold.

4. *Selection and Recombination*: select parent individuals and apply genetic operations(crossover, mutation) until a new generation of population is filled and replace the old population. This process is very important as it might creates/improve/remove solutions in order so that there might exit some fitness values that move closer to the ideal solution.

Once the result after the iteration met the termination criteria, the solution obtained is the one from the current population with the highest fitness value.

2.2 Linear Genetic Programming

Linear genetic programming (LGP) [14, 9] is a variant of EA. The differences are that the representation of individual solution has changed to program structure instead. Generally speaking, we are now trying to evolve and search for programs as our final solution.

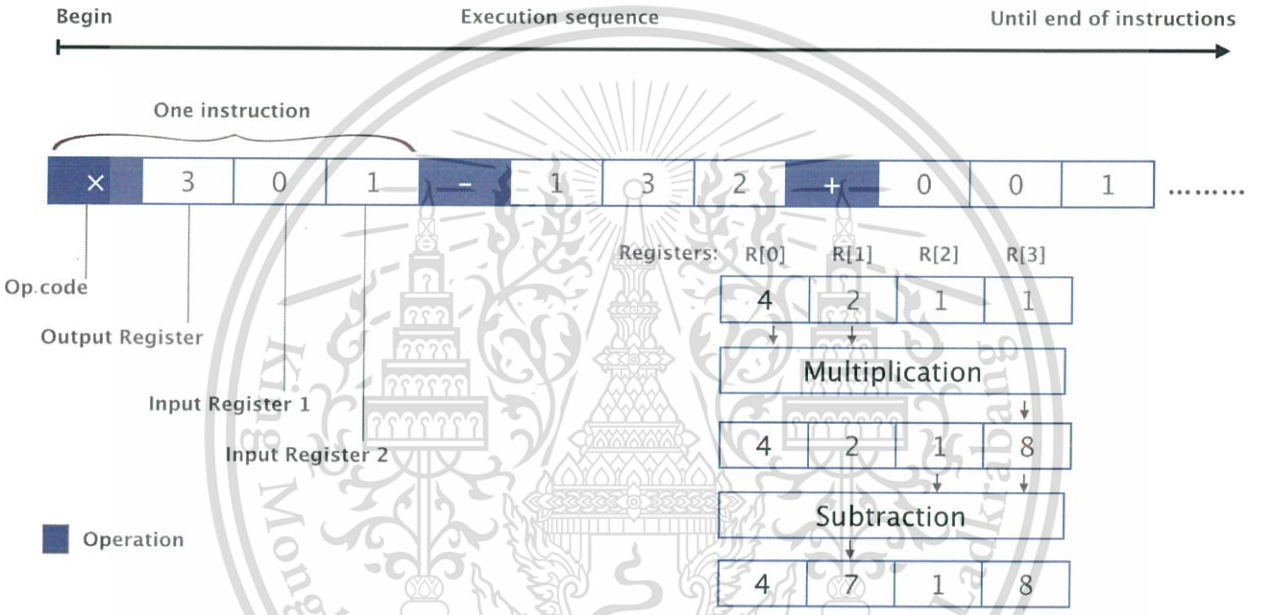


Figure 2.2: Linear program representation and execution

In this particular case, the program are depicted as a linear sequence of instructions that indicates what operations to be performed (Fig:LGPProgramExec). However, to execute an operation, it needs a place holder to fetch input from and to store the output of the operation. Therefore, set of registers are added to fill in the gap as a temporary storage. Therefore, an instruction consists of: Operation, Input1, Input2 and output. The latter three are the number of register indexes.

2.3 Multi-Objective Genetic Algorithm

Multi-objective genetic algorithm (MOGA) [15] can also be called a variant of EA as well. The mechanism undergone modification so that the solutions are ones that solve multiple objectives. From this point, it is obvious that each solution in MOGA now has multiple fitness corresponding to the number objectives.

However, because of the number objectives are now more than one, there usually exists a certain group of solutions which cannot be judged to be better than the others. This results from the distribution of fitness values in one solutions is not equal. In this case, the result of the evolution is not a single individual solution but set of elite individuals called pareto-optima.

2.4 Digital Image

Originally, an image can be represented as a continuous mathematical function. Real world image has a continuous property and large infomation load. Therefore, in order to make computers be able to perceive images, the real world image is digitized into a digital image instead. Image digitization consists of two steps [13]; sampling and quantization. In sampling step, the continuous image function is sampled into a matrix of M rows and N columns in a position that correlate to the real world version of the image. A sampling points in the matrix is called a pixel as the smallest unit. The higher sampling rate is better becaues the digital image contains more information and details which close to the real workd image but it might consumes more space in the data storage. After the sampling comes the quantization step. In this step, an integer value is assigned to each pixel that represents the value at each sampling point. In short, the continuouse value at the sampling point is being converted into appropriate corresponding number that high enough for human perceptions.

2.5 Image Processing

Generally speaking, image processing process concerns changing properties of an image to make some information in the image becomes more interpretable by humans [1]. It can also be used for convert the information in an image to an appropriate form so that machines can perceive. In this

research, the input image is a digital image where computers change the properties or nature of the image.

CHAPTER 3

METHODOLOGY

3.1 Applying Linear Genetic Programming

3.1.1 Program Representation and Execution

In this research, a program is a sequence of instructions. Each instructions indicate an operation to execute including inputs and output specifications. The available operations to create each instruction are selected from a set of operations or operation pool.

In this manner, the execution of a program is the process of decoding and executing each instruction sequentially. The process is complete if and only if the last instruction is executed successfully.

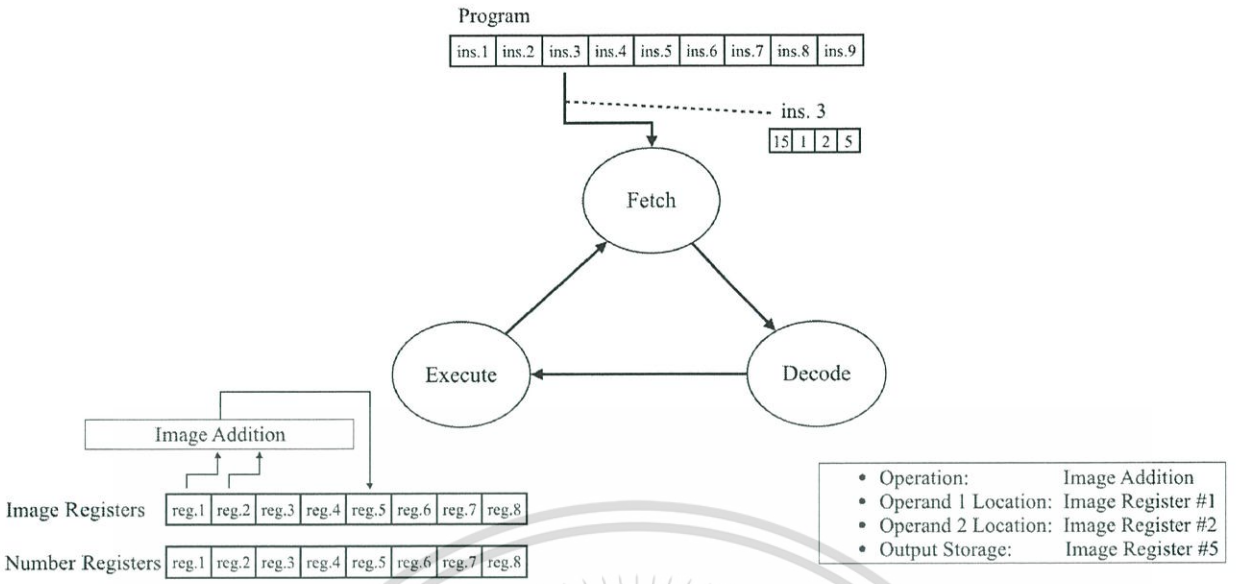


Figure 3.1: Program execution process

As this research focus on object classification system, the operation pool to compose an instruction is consists of several primitive image processing operations. Naturally, Inputs and output data type can be either image or real value. All of primitive operator used in this research are categorized as displayed in Table 3.1.

Because of the fact that there are now real number value and image value data to work with, the registers for storing inputs and output in LGP process are now divided into real number registers and image registers as each operation can require either type of data to work with.

3.1.2 Program as Feature Extractor

(refer to object classification process) In this work, the feature extractor is a simple program as described previously. The feature extraction process is assumed to produce a feature map. Once the input image is fed into the process, the program is executed upon the image. In more details, the input image is used as initial values of image registers before the execution. For diversity, grayscale, red, green, and, blue color band version of the input image are used partially in image register initialization. After successful execution, the final values in the registers are used to create feature maps.

In this way, the program successfully act as a feature extractor which create feature maps from

the input image and further forward them to classifier to produce classification results.

To elaborate the role of a program in typical object classification process (refer to object classification process), the example task are assumed. The main objective of the example task is to classify a pixel of liver fibrosis image. The provided training data is a set of liver biopsy images with it's grayscale image groundtruths. Therefore, the actual groundtruth of each pixels in original image will be described as the intensity value of grayscale intensity value of the same pixel coordinate.

(a) Raw Image (b) Groundtruth

Figure 3.2: Original image and it's respective groundtruth of example task

Supposedly, our task is to classify each pixel into different categories. The training data is a set of images including their respective set of groudtruths. The feature extractor will be executed on each training data. Each time an image data is fed into the process, the current training image will be stored in every image register as initial data. However, a few registers can also store red, green, blue, or grayscale version of the original image for the sake of diversity in information. The program will be executed as described in Section 3.1.1. After the execution, the results left stored in the registers will be used to create feature map and forward it to train the classifier.

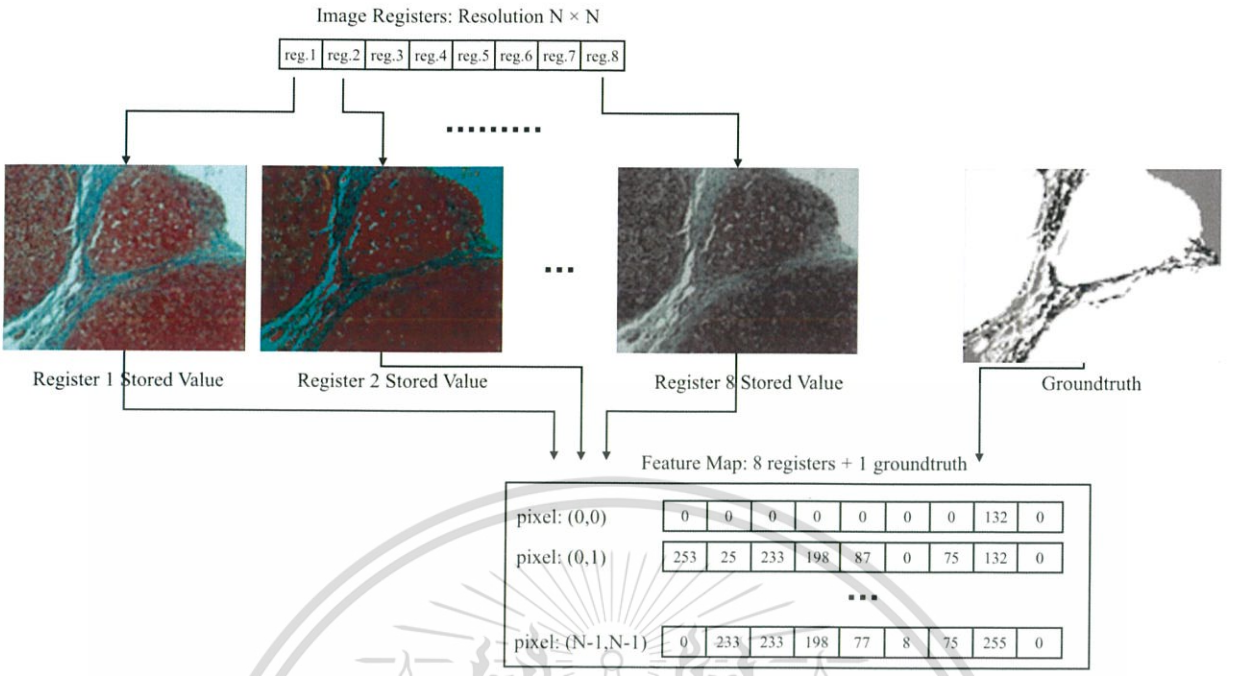


Figure 3.3: Feature Map Creation Process

3.1.3 How Linear Genetic Programming Find an Optimal Feature Extraction Program

Initially, a fixed number of programs are randomly generated and thus, resulted in initial population. As previously mentioned, A program generated in this work is represented as a sequence of instructions. This is partly because LGP already generate the solution in this manner.

To evaluate each program, a performance value or fitness is set as standard measure. In this particular case, the solution program will be used as a feature extractor in typical object classification procedure. Therefore, we will assume that the performance of classification with the obtained feature extractor also reflects the performance of that feature extractor as well.

The program will be put to the test by letting it perform in the classification system environment. The set up consists of a training data, and a classifier (untrained). Every program will be put to the test by performing as feature extractor in this set up and the result will be recorded as each individual's fitness.

At the end of each execution, There will be processed images left within the image registers. The feature map initially include the label of every pixel. Therefore, for every label, the pixel value

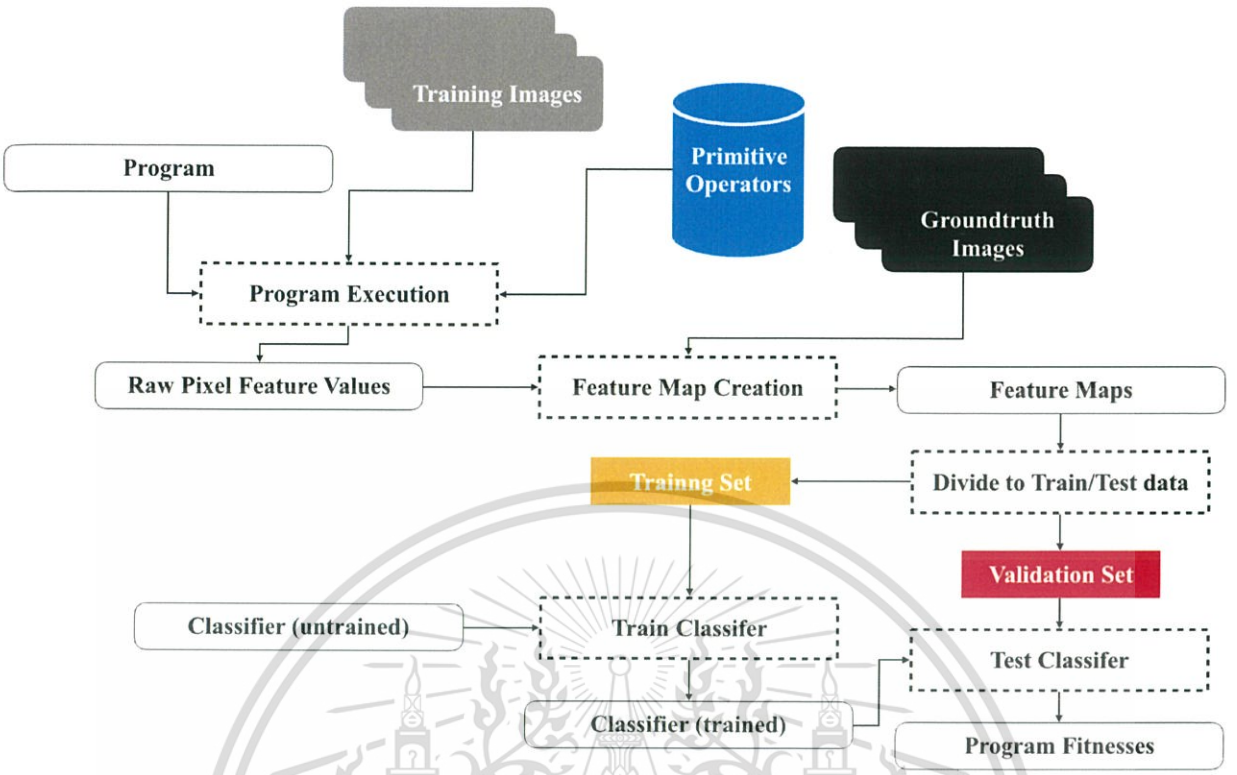


Figure 3.4: The Illustration of Program Evaluation Process. Classification Simulation with a Program. The Result is Program Fitness Which Reflects the Feature Extraction Ability of The Program.

with the same pixel coordinate as the label will be mapped to that particular label. If there are 8 image registers, a single pixel label which has coordinate (x,y) will be mapped with 8 different pixel values with the same coordinate (x,y).

The next process after all programs in a population are evaluated is to *evolve* the populations. A new offspring populations are created by combining different parts of previous population members. A pair of candidate programs within the same population are selected based on their fitness values and create new pair of offspring programs using *one-point crossover* [16] (Fig:OnepointCrossover). A part of parent programs are exchanged at randomly selected joint controlled by crossover rate parameter. However, the crossing point. However, there will not occur a complete switch between program.

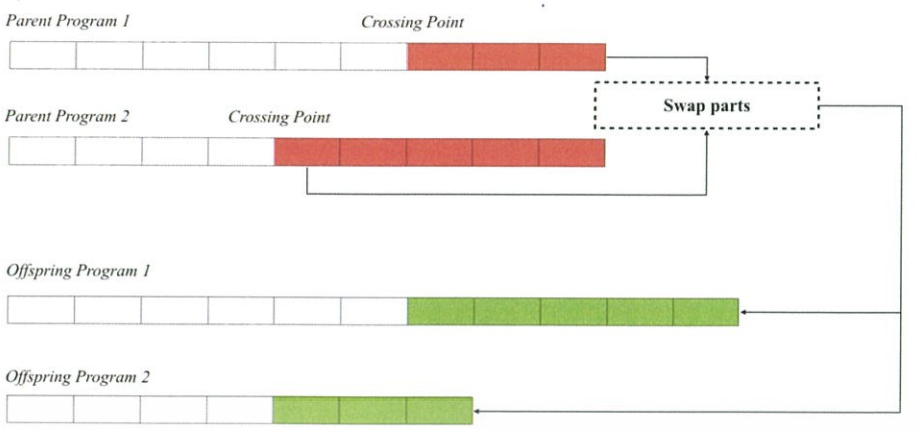


Figure 3.5: One-point crossover

Before beginning the new iteration, each program will have a chance to *mutate* by mutation operator. In summary, a part of instruction in a program might get modified which is a simple mechanism to create diversity within the new population. However, not all programs can mutate. The chance of program getting mutated is controlled by mutation rate parameter.

3.1.4 Non-dominated Sorting Genetic Programming II

Apart from using the standard selection and recombination procedure in EC, another algorithm was applied in this research to enhance the selection and recombination process of MOGP called non-dominated sorting genetic programming (NSGP-II) proposed by K. Dep [6]. The core of the algorithm is to maintain the diversity of programs in offspring population while preserve elite programs which had good evaluation results among the other programs within the parent population.

At the beginning, a new offspring population is generated using standard selection and recombination procedure. After the offspring population was evaluated, the offspring will be merged back into parent population. The result is a pool of programs twice the member of usual population capacity. Then, each program will be assigned ranks based on their dominance.

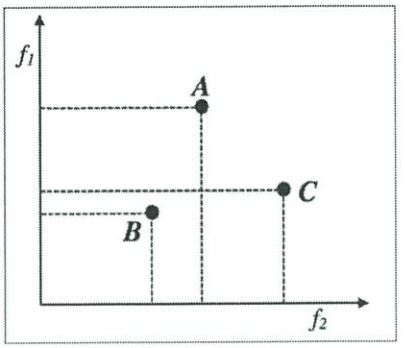


Figure 3.6: Example of three individual programs with fitness f1 and f2. The programs A and C are assigned the same ranks and program B has lower rank than A and C (assumes that f_1 and f_2 are for maximization objectives)

Figure 3.6 depicts the example scenario when comparing programs in MOGP in which one can have many fitness values. After each programs' rank are determined, the example of the resulted population after non-dominated sorting is shown in Figure 3.7. Assuming that f_1 and f_2 is fitness values for maximization objectives, green labelled programs are considered the first rank and will be selected for creating actual offspring population. If the current offspring population capacity is not full, the next highest rank programs are selected next. In addition, the extreamum are guaranteed to be selected in order to maintain diversity within offspring population. The extreamum is a program which possess unlikely the highest value of single fitness.

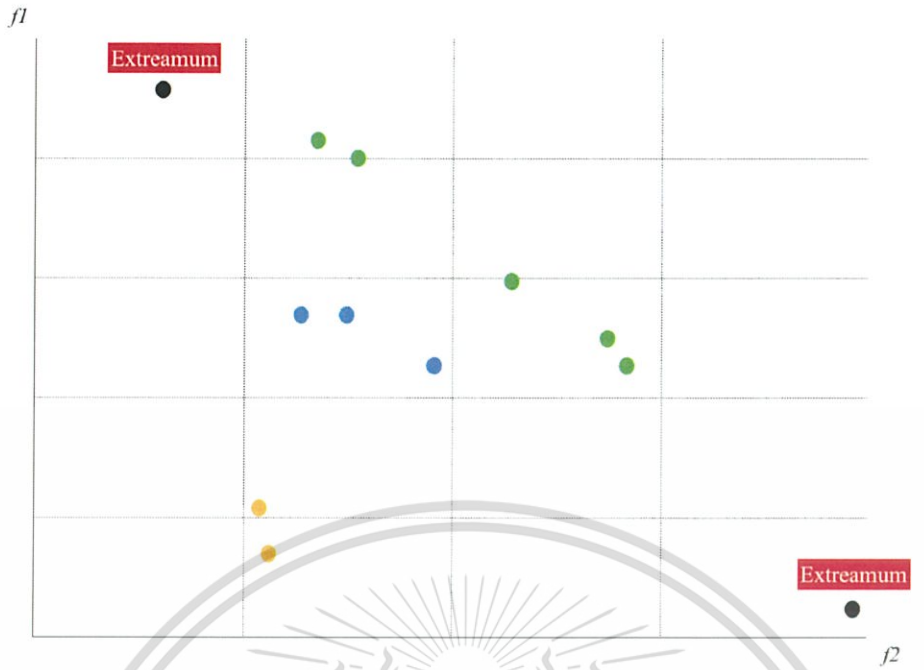


Figure 3.7: Several Individuals are sorted based on their dominance. Programs with the same color is considered to be in the same rank.

3.1.5 Transfer Learning

To understand where the ideas of transfer learning in this work, the best possible way is to make an example when an individual is solving one big problems consists of multiple possible tasks. For example, classifying a group of objects into multiple categories. In this case, the individual needs to learn the specific of each object class's characteristics from scratches one by one. This process is huge and requires time to overcome this learning curve.

As a result, it would be more convenient to at least inject an existing knowledge about a subset of all categories before start figuring out the whole set. Instead of trying to classify an object class apart from all the others, it might be easier if the we can make comparison in smaller groups. Like divide an conquer schemes, all the object classes are divided into the smallest groups it can be divided. Then, the classification process will starts from learning the characteristics pf each smallest groups and how to differentiate each of them in a very small domains. When we obtained the knowledge of how to classify objects within a small groups then we can try to classify a slightly larger group of categories. This process is easier than normal methods because the profession for each small tasks are shared and being used while figuring out the larger category domain.

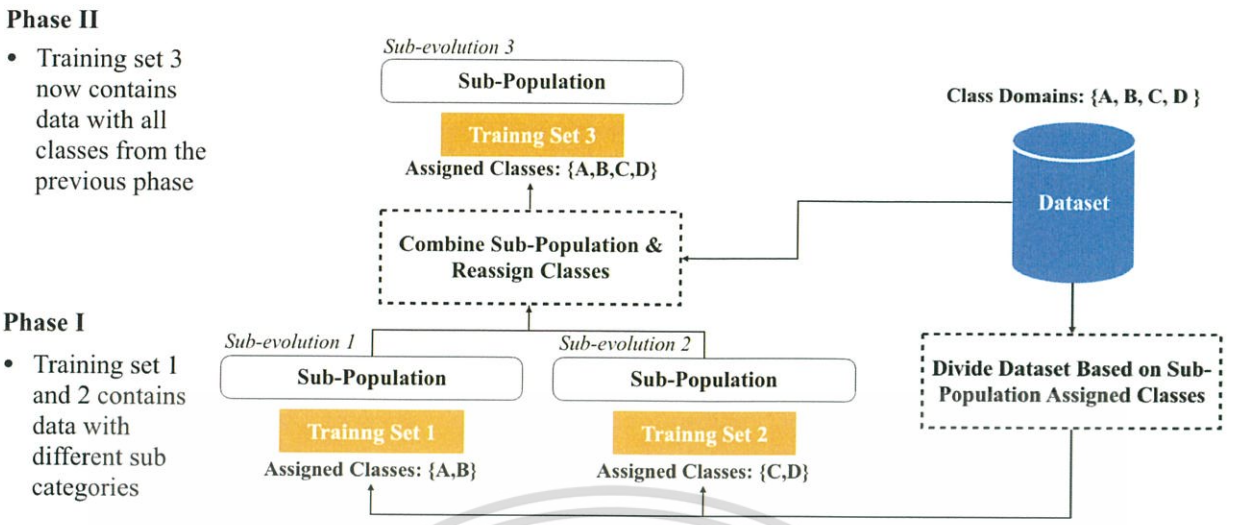


Figure 3.8: The Illustration of transfer learning architecture

Ultimately, the benefits we can obtained by this transfer learning method is that the evolution process easily discover the programs which yields good fitness values by using possibly using smaller set of training data.

From Figure 3.8, to apply transfer learning, the entire evolution process are divided into phases in which they contain it's own sub-evolution. The population of programs and classification tasks are assigned into group of sub-evolution. After every sub-evolution in a phase is complete, the remaining sub-population is combined into bigger population and being assigned bigger classification based on each population's profession. Then the next phase can begins it's own sub-evolution.

Table 3.1: List of primitive operators

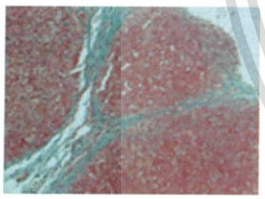
One-input operators	**Two-input operators**
image → image	**image, image → image**
highpass filter	image addition
Sobel operation	image subtraction
image negative	**image, real value → image**
mean thresholding	lowpass filter
entropy thresholding	median filter
histogram equalization	morphological dilation
grayscale conversion	morphological erosion
RGB conversion	morphological opening
HSV conversion	morphological closing
HSL conversion	local histogram equalization
LAB conversion	thresholding
LUV conversion	local variance
image → real value	local skewness
global mean	local kurtosis
global variance	local maximum (max filter)
global standard deviation	local minimum (min filter)
global skewness	local mode
global kurtosis	local range
global maximum	local entropy
global minimum	
global median	
global range	

CHAPTER 4

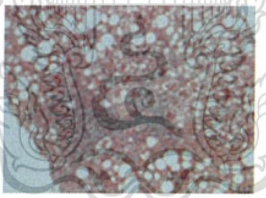
EXPERIMENTAL RESULTS AND DISCUSSIONS

4.1 Fibrosis Dataset

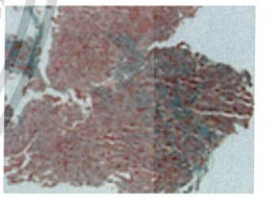
Liver biopsy image analysis in this research prioritizes on segmentation of fibrosis tissue. It can be used in medical assessment to determine the severity of damage occurred in the liver. From this step, further medical treatment plan can be decided.



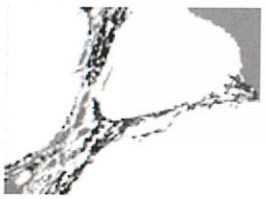
(a) Raw Image 1



(b) Raw Image 2

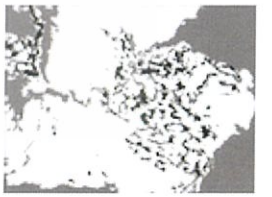


(c) Raw Image 3



(d) Groundtruth Image 1

(e) Groundtruth Image 2



(f) Groundtruth Image 3

Figure 4.1: Sample Data of Liver Biopsy Image with It's Respective Groundtruth

To achieve the goal of this research, experiments have been conducted with a dataset of liver biopsy images used in Meejaroen et al.'s work [30]. The dataset consisted of 10 training images and 22 test images. The images were resized into 128×64 pixels. The quantity of fibrosis in an image varied from 2.36 to 22.21%.

4.2 Tools and Languages

In this research, the automatic construction of feature extractor method using MOGP was implemented in C++ language on Microsoft Visual Studio 2017 for Windows 64 bit. The primitive image processing operators were implemented using C++ OpenCV library version 2.4.9 which is a library providing several pre-implemented image processing functions, image data storage and some machine learning tools such as Bayesian classifier.

4.3 Parameters

The information observed from each biopsy images are background, normal tissue, and fibrosis tissue. Thus, the groundtruths also labelled accordingly. The measurement for this problem included measuring amount of fibrosis tissue so that treatments can be applied appropriately. Therefore, other than original measurements, average fibrosis percentage error was added to complete the evaluation. Precision, Recall, and Accuracy were added to support the evolutionary process and make sure that the programs follow the rules of image classification as they evolves.

Table 4.1: Global Parameters For Fibrosis Problem

Number of Classes	3
Performance Metrics	Precision
	Recall
	Accuracy
	Average Fibrosis Percentage Error
Image Size	640 x 480
Image Resize	128 x 96

Table 4.2: Parameter for sub-evolution of Fibrosis experiment Phase 1

Phase 1	**Population size**	50
	No. of sub-evolution	3
	Generation	100
	NSGP-II	Enabled
	Crossover rate	0.8
	Mutation rate	0.3
	Selection type	Tournament by Accuracy
	Assigned classes	Partial, Permutation
	Images	10
	Training samples	122,880
	Tran/Test ratio	0.5
	Total execution	7,500,000

Table 4.3: Parameter for sub-evolution of Fibrosis experiment Phase 2

Phase 2	**Population size**	150
	No. of sub-evolution	1
	Generation	10,000
	NSGP-II	Enabled
	Crossover rate	0.8
	Mutation rate	0.3
	Selection type	Tournament by Average Fibrosis Percentage Error
	Assigned classes	All
	Images	10
	Training samples	122,880
	Tran/Test ratio	0.5
	Total execution	15,000,000

The evolution parameters are varied by different phase. For this problem, the evolution were divided into 2 phases. Phase I contains 3 sub-evolutions. Sub-evolution 1 assigned classes were background and tissue. Sub-evolution 2 assigned classes were background and fibrosis. Sub-evolution 3 assigned classes were fibrosis and tissue. The architecture of transfer learning for this problem is displayed in Figure 4.2

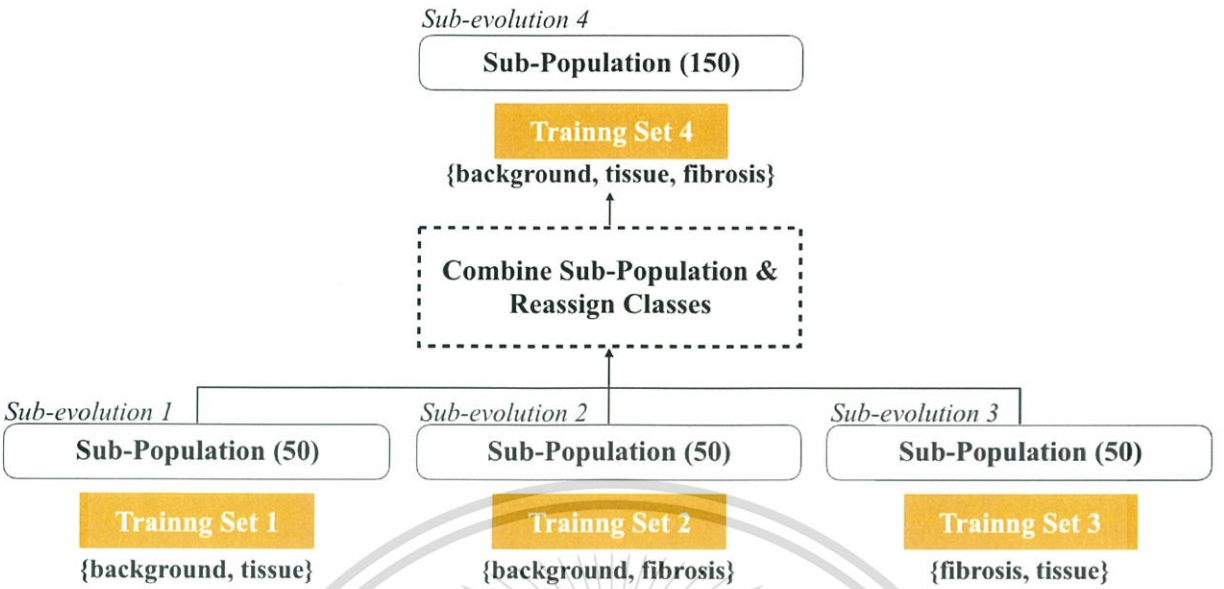


Figure 4.2: Transfer Learning Architecture for Fibrosis Detection Problem

4.4 Fibrosis Experiment Results and Discussions

4.4.1 Proposed Method and Manual Approach Comparison

In this section, the proposed method which is an automatic feature construction approach is compared with the manual feature construction approach by Meejaroen's et al [30].

In their work, color information was used in order to classify liver fibrosis pixel in liver biopsy images. First, the input image would go through color enhancement. Next, low pass filtering will be applied to the enhanced image. Then using the method from Sumitpaibul et al [38] to perform background segmentation. Classifier classify the RGB color value of each pixel.

The classification results were used to compute fibrosis percentage error in which the proposed method also used as one of the performace metrics.

$$\begin{aligned} Percentage\ of\ fibrosis\ (PoF) &= \frac{n_f}{n_f + n_t} \times 100, \\ Fibrosis\ estimation\ error &= \mid PoF_p - PoF_{gt} \mid, \end{aligned} \tag{4.1}$$

where n_f and n_t denote the counted fibrosis pixels and normal tissue pixels, respectively while

PoF_p and PoF_{gt} denote the percentage obtained from the segmented image using proposed method and the one from its ground truth image, respectively.

Using the parameter lists in table 4.2 and table 4.3, the evolution process of proposed method were executed for 10 separate runs for stability. Then, the best program out of every trials was chosen to compare with non-automatic approach.

In table 4.4, Statistical test for P-value was conducted. The null hypothesis(H_0) in this case was that the mean value for average fibrosis percentage error is less than or equal to Meejaroen's Bayesian method fibrosis error result which was 2.63. The P-value obtained statically supports the null hypothesis. In this experiment, the proposed method which is an automatic approach statistically outperform the non-automatic method by Meejaroen's et al.

Table 4.4: Selected Programs from Each Trials of the Proposed Method and the Result of Non-automatic Approach from Meejaroen's et al[30].

Run	Precision	Recall	Accuracy	Avg. Fibrosis Error
1	52.31	52.81	92.08	**2.32**
2	52.22	48.88	91.83	**2.28**
3	52.36	52.20	91.78	**2.58**
4	48.21	57.12	91.15	3.19
5	60.06	52.26	**92.78**	**1.90**
6	57.17	55.14	**92.87**	**2.13**
7	50.59	57.58	91.89	2.75
8	50.82	51.30	91.62	**2.41**
9	53.80	52.23	92.10	**2.56**
10	56.36	56.44	**92.63**	**2.43**
Mean				2.45
Variance				0.12
P-Value (One-Tail)				**0.077**
Meejaroen et. al[30]	65.13	59.64	92.23	2.63

4.4.2 MOGP (without Transfer Learning) and Proposed Method (with Transfer Learning) Comparison

To measure the performance of the proposed method. The normal approach which use MOGP without transfer learning (dubbed MOGP) were executed 10 times same as with proposed method. The parameter for the benchmark method was the same with Table 4.3.

The MOGP method is the automatic approach used in our previous work [44] which produced programs with low fibrosis percentage error. In this work, the method was studied further if the efficiency can be improve using transfer learning. Thus, the comparisons were made. The MOGP method will used the parameter in Table 4.3

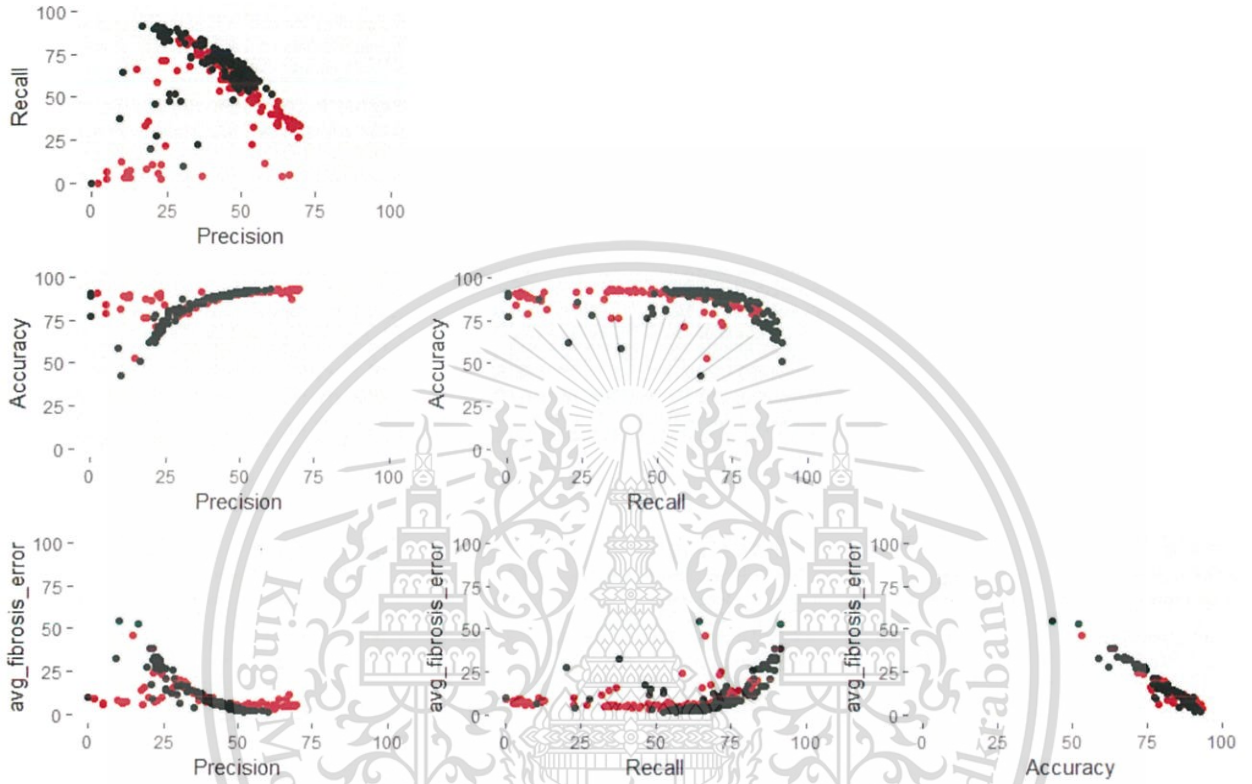


Figure 4.3: Comparison from One of The Best Selected Run between Non-Transfer Learning Method (Red) and Proposed Method (Black)

The result of applying the proposed method to solve this problem were represented in partial dependency graph as depicted in figure 4.3. The black dots represent each individual program of the proposed method while red dots represent MOGP programs. Each dots were plotted based on it's fitness values which are divided into different comparisons sub-graph. For each comparison, the optimal results were expected to reach larger objective values which applied to maximization objective. However, for any comparison involving average fibrosis percentage error are expected to have small objective values because it is a minimization problem.

The results of the comparison is very competitive. However, The programs generated yields mostly positive fitness shape. In this particular run, the proposed method fell behind MOGP in

term of precision and recall but performs better on accuracy and average fibrosis error which more or less has higher quality. In contrast to the other proposed method results which mostly fell behind with precision and recall while achieve comparable performance on both accuracy and average fibrosis percentage error.

Table 4.5: Summary of Optimal Values Found in All Fibrosis Experiments (Proposed Method)

(%)	Precision	Recall	Accuracy	Average Fibrosis Percentage Error
Min	0.00	0.00	13.55	1.90
Max	79.38	95.02	93.56	89.44
Average	32.95	50.29	80.74	14.24

Table 4.6: Summary of Optimal Values Found in All Fibrosis Experiments (MOGP Method [44])

(%)	Precision	Recall	Accuracy	Average Fibrosis Percentage Error
Min	1.76	0.00	8.67	2.60
Max	80.18	99.98	93.20	90.33
Average	39.40	58.06	83.86	12.60

Table 4.5 shows the maximum values found throughout all fibrosis experiments. The maximum value achieved for precision was 79.38%. The maximum value achieved of recall was 95.02% and The maximum value achieved of accuracy was 93.56%. Finally, The minimum value achieved for average fibrosis percentage error was 1.9. On the other hand, maximum value of precision found in MOGP run was 80.18%. Maximum recall value is 99.98% which accuracy is less than proposed method at 93.20%. Finally, the smallest fibrosis error achieved is 2.60 which is quite a gap between proposed method.

Table 4.7: Best Individual on Fibrosis Transfer Learning Experiments (Proposed Method)

no.	Precision (%)	Recall (%)	Accuracy (%)	Avg. Fibrosis Error
1	52.31	52.81	92.08	2.32
2	52.22	48.88	91.83	2.28
3	52.36	52.20	91.78	2.58
4	48.21	57.12	91.15	3.19
5	60.06	52.26	92.78	1.90
6	57.17	55.14	92.87	2.13
7	50.59	57.58	91.89	2.75
8	50.82	51.30	91.62	2.41
9	53.79	52.23	92.09	2.56
10	56.35	56.43	92.62	2.43

Table 4.8: Best Individual on Fibrosis Transfer Learning Experiments (MOGP Method)

no.	Precision (%)	Recall (%)	Accuracy (%)	Avg. Fibrosis Error
1	52.20	59.73	91.92	2.60
2	51.24	22.35	91.25	6.65
3	57.18	59.87	92.47	2.64
4	43.49	70.77	89.29	6.34
5	54.49	55.6	92.25	2.77
6	47.21	48.28	91.33	2.82
7	56.91	50.27	92.17	3.21
8	60.39	48.55	92.40	3.71
9	48.59	41.70	90.44	3.10
10	64.12	47.14	90.91	2.67

Table 4.7 showed selected program based on average fibrosis percentage error, the absolute objective for this problem. From both table, as previously mentioned, the results show the disadvantage in stability of the proposed method while displaying the sustainability in producing lower value of average fibrosis percentage error. In addition, the accuracy results of programs from both approaches were highly competitive. The statistical comparison of fibrosis error is depicted in Table 4.9 with current hypothesis as the MOGP method performs better than the proposed method on average. The result P-value is 0.018 which rejected the null hypothesis. In other words, the MOGP which include transfer learning was able to outperform the standard MOGP approach statistically.

Table 4.9: Comparison using P-Value with Significance Level 0.01

no.	Proposed	MOGP
1	2.32	2.60
2	2.28	6.65
3	2.58	2.64
4	3.19	6.34
5	1.90	2.77
6	2.13	2.82
7	2.75	3.21
8	2.41	3.71
9	2.56	3.10
10	2.43	2.67
Mean	2.46	3.65
Variance	0.13	2.36
P-Value (One-Tail)	**0.018**	

Figure 4.4 represents the comparison of fitness growth and program discovery between the normal MOGP method which have normal architecture but with the same measurements and the proposed method (with transfer learning).

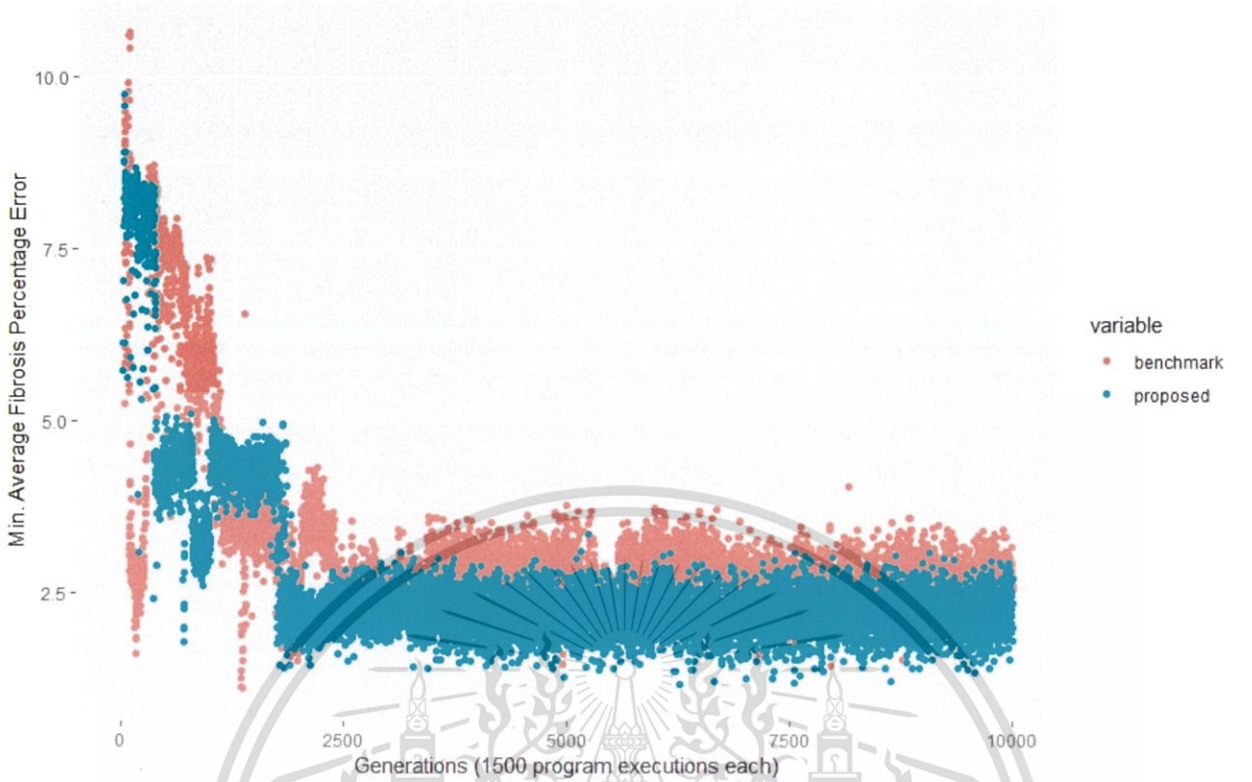


Figure 4.4: Comparison of Benchmark and Proposed Method (Best Selected Run) Against Program Execution Number (Fibrosis Error)

The fitness values from the proposed method side outperform the original benchmark in achieving low average fibrosis percentage error. Between 0 to 3,750,000 program executions (0 - 2500 generations), the result heavily fluctuates before reaching the stable results after. At first, the benchmark method discovered a lot of optimal solutions which is faster than the proposed method. However, the solution appeared struggling to persist through the evolution and were eliminated shortly after. In contrast to the proposed method which found fewer optimal solutions but ultimately reached a stable state slightly faster than that of benchmark. Furthermore, more optimal solutions were discovered and some might had persisted far throughout the evolution because more and more optimal solutions were discovered at frequent rate. In this case, the proposed method achieved better frequency in solution discovery.

One noticeable difference between the proposed method and benchmark method is that the proposed method's program fitness doesn't scatter around as much as benchmark's program fitness. In this case, the proposed method performed well in preserving the current optimal values. However,

the other take away would be that the sharp drop and rise of optimal fitness values itself contribute to the fact that it can outperformed the proposed method in accuracy, precision, and recall.

In general, the proposed method and benchmark method both struggles to maintain the balances between each objectives. A pattern of programs were speculated based on it's objective values. There are programs which maintains the balance between precision and recall. This type of program tends to achieved overall optimal fibrosis error. The proposed method selected individuals were found to contains most of programs with this type. However, the programs which fails to balance both tend to have less optimal fibrosis error in most cases. The balance between precision and recall might be a part of the knowledge passed between each phases while trying to classify each pair of object classes. In simple terms, the proposed method might takes more time balancing each objective values which causes overall fitness of the selected individual to be lower but with less gap. In doing so, the result displays the ability to evolve programs of proposed method could discover higher potential programs based on average fibrosis percentage error.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

The purpose of this work is to develop an automatic feature extraction program using genetic programming. During the process, transfer learning and multi-objective mechanism were also provided to support the feature construction process.

The proposed method achieved better performance in terms of average fibrosis percentage error. In addition, the evolution process can discover potential programs earlier than the benchmark method which didn't apply transfer learning. The discovery rate of the propose method also achieve more stable result. Furthermore, the evolution process of the proposed method may potentially reduce the amount of data processing in the earlier stage because the beginning phase of evolution requires only a specific set of data classes for each sub-evolution.

The result of applying the proposed method with Fibrosis dataset shows the advantages of applying transfer learning schemes into evolution process. The lowest average fibrosis percentage error obtained is 1.9 which is less than the lowest of the approach without transfer learning of 2.60.

Transfer learning is not a new concepts but offer advantages in solving real world problems. However, a lot of potentials in transfer learning is left to be explored deeper. The transfer learning schemes used in this research made based on the divide and conquer concepts which is not very complex to implement. However, the experiment result still shows improvement.

In the future, an EC based approach with more complex and intricate system of transfer learning schemes might further encourage the results of quantifying liver fibrosis and contribute to saving lives and improving living conditions for patients. .

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APPENDIX

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Detection of Fibrosis in Liver Biopsy Images Using Multi-Objective Genetic Programming

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***Abstract*—This paper proposes an automatic construction of feature extractor for liver fibrosis detection using a multi-objective genetic programming approach in which a constructed feature extractor was measured in different aspects in which becomes the objectives of the evolutionary run. The result of the evolutionary run is a set of solutions with different strengths and weaknesses. A solution from each experiment is selected and compared with a benchmark handcraft method in by each experiment and top-five manners. One of the best result obtained has 2.09 fibrosis estimation error which is less than the benchmark method with 2.63 fibrosis estimation error.**

***Keywords*—liver biopsy; liver fibrosis; image analysis; genetic programming; feature synthesis**

I. Introduction

The liver is one of vital organs in human body, which has a variety of functions, for example, detoxification, production of necessary biochemicals, being a storage of various substances such as glucose and vitamins. However, the liver is prone to many diseases including fatty liver, which is an excessive accumulation of fat in liver cells, or cirrhosis, which is an irreversible replacement of liver tissues by fibrosis. These harmful diseases develop slowly but often have no obvious symptoms unless the liver has been largely damaged. Consequently, an early diagnosis of the diseases would greatly prevent patients from death.

Medical imaging devices such as microscope, Computed tomography (CT) scanner, Magnetic resonance imaging (MRI), or ultrasound sensors have become beneficial tools to reveal abnormalities occurred inside the liver. However, medical images, which usually contain a huge amount of information, are sometimes difficult to interpret and required a lot of expertise. Nowadays, image analysis techniques have been applied to help doctors diagnose liver diseases from medical images. Ribeiro et al. developed a computer-aid diagnosis system to classify steatosis in the liver using ultrasound images [19]. Huang and Lai presented an image segmentation technique based on support-vector machines (SVMs) to locate nuclei cells in liver biopsy images [7]. Gordan et al. studied about image segmentation of liver fibrosis in JPEG compressed liver biopsy images [6]. Vicas and Nedevschi utilized an ultrasound simulation software for fibrosis detection [26]. Kayaalti et al. reported the feasibility of using texture properties from liver CT images to determine the fibrosis stage [8]. Masseroli et al. presented an image analysis system for automatic quantification of liver fibrosis [15]. Lin et al. showed that color information could be a reliable tool for automatic separation of liver fibrosis areas [14]. Meejaroen et al. proposed a technique based on a Bayesian classifier to detect and quantify fibrosis areas in liver biopsy images [16]. Sumitpaibul et al. proposed an image analysis method for detecting fat in liver biopsy images [24].

However, these image analysis methods were usually handcrafted by human experts. It may be prone to error and require extensive studies and evaluation of experiment results. Evolutionary computation (EC) has been used to solve image analysis problems, which is an optimization method that borrows the concept of Charles Darwin's evolution [2]. One of the earliest applications of EC in this field date back to 1996 [18]. In addition, EC itself has been developed over the years and has many variants and improvements. Nevertheless, many researchers have been using different kinds of EC to overcome problems in usual image analysis tasks by developing an automatic construction of image analysis methods.

From the literature, several kinds of EC were used. Genetic algorithm (GA) emphasize the traditional EC process. Genetic programming (GP) is one of the most common variant of EC. It represents the solution as a program with tree-based structure. Linear genetic programming (LGP) changes the representation of the program into a form of linear instruction instead. Multi-objective genetic programming (MOGP) was developed so that the evolutionary process fulfills more than one objective. There are many more extensions for EC and some of them are modified or combined with other algorithm to solve image analysis problems.

Nagao and Masunaga used GA to evolve an image feature construction process from image processing filters [17]. Lin and Bhanu used GP to construct a composite operators using primitive image operators [13]. Song and Ciesielski utilized GP to construct classifiers for texture classification and segmentation of bitmap texture image [22]. Trujillo and Olague introduced several image processing operators using GP-based approach which detect interest points in an image [25]. Watchareeruetai and Phanjan used LGP to evolve contour that recognize leaf shape [28]. Krawiec and Bhanu applied cooperative coevolution to standard evolutionary algorithm to build image feature extractor program [11]. Watchareeruetai et al. demonstrated the capability of canonical transformation applied to evolutionary algorithm in one of his work which is about utility of MOGP for constructing feature extractor [29], [27]. Shao et al.'s feature descriptors were constructed using MOGP by combining different 2-D image operators [20]. Suganuma and Nagao utilized GP to construct features using

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multi-layer architecture of image operation and transformation approach [23]. Lilywhite et al. applied evolutionary method to construct features for object recognition tasks [12].

This paper focuses on the automatic construction of feature extractor using LGP in order to detect fibrosis area in the liver which is vital for human health and living conditions. The proposed method considers multiple aspects to measure the effectiveness of the discovered solutions. Therefore, multiple objectives need to be set-up to represent these aspects and GP is responsible for optimizing these objectives. The key contributions of this paper are that 1) by using MOGP, multiple different solutions can be explored as a result of one single run. 2) Given a dataset, the feature extractor construction process is automatic and requires no further human input. 3) A solution are measured by considering five different objectives to guide the construction process and ensure the performance of the final results.

The remaining of this paper is organized as follows: Section II explains the detail of the proposed method; Section III presents experimental results and discussion; Section IV concludes the paper.

II. Automatic Construction

The proposed method receives an image as input and produces the segmented image version as output. The main component consists of a feature extraction program and classifier (pixel-wise).

In this work, a feature extraction program is a sequence of primitive image processing operations. The result of the execution is a set of features which represents properties of a pixel. Therefore an input image with 128×96 resolution must have 12,288 features corresponding to each pixel. The classifier will be used to classify each feature set into one of three different classes: fibrosis tissue, normal tissue, and background. These classes correspond to the pixel the current feature set represent.

The feature extraction program is built automatically using EC, specifically, LGP [1]. The overview of the proposed method is shown in Fig. 1.

A. Program Representation

The program in LGP is represented as a sequence of instructions. Each instruction specifies the operation to be executed as well as its input(s) and output. The execution of a program requires a set of registers as a temporary storage for the program to store input and output. The program execution is performed sequentially as shown in Fig 2. The execution starts from the first instruction until the last one. This manner of execution is also similar to that in a micro-controller [1].

In addition, given the fact that the operators are primitive image processing operators. There are two different kinds of register: 1) numeric register which stores numerical value 2) image register stores image data.

B. Primitive Operators

The operations denoted in each instruction are selected from the specified pool of standard image processing operators [5]. The list of primitive operators is listed in Table I.

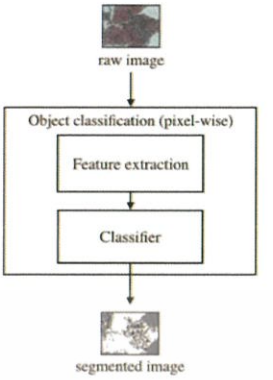


Fig. 1. The overview of the proposed method

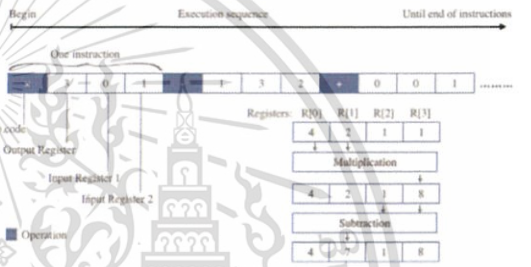


Fig. 2. An execution process of a single program

C. Genetic Operators

EC adapts the concept of natural selection to create new offspring using genetic operators [10]. This is also true for its variant algorithm, GP.

Selection operation in this research uses random selection instead of standard evolutionary manner, e.g., tournament selection. This is the first standard step in creating an offspring population. The operator selects a pair of programs (in this case, random) as parents for crossover operation.

Crossover operation is performed after the selection operation. In this research, one-point crossover is applied by randomly choosing a cutting point from both program. The part after the cutting point from both of them will be swapped. The probability of crossover occurrence frequency is controlled by crossover rate.

After the crossover operation, mutation operation is performed. An individual's genes have a chance to be inserted, deleted or undergone some modification (in this scenario, genes of an individual are the sequence of instruction of a program). This is the process that increases the diversity element of the programs created. The probability of mutation occurrence frequency is controlled by mutation rate.

TABLE I. LIST OF PRIMITIVE OPERATORS

One-input operators	Two-input operators
image → image	**image, image → image**
highpass filter	image addition
Sobel operation	image subtraction
image negative	**image, real value → image**
mean thresholding	lowpass filter
entropy thresholding	median filter
histogram equalization	morphological dilation
grayscale conversion	morphological erosion
RGB conversion	morphological opening
HSV conversion	morphological closing
HSL conversion	local histogram equalization
LAB conversion	thresholding
LUV conversion	local variance
image → real value	local skewness
global mean	local kurtosis
global variance	local maximum (max filter)
global standard deviation	local minimum (min filter)
global skewness	local mode
global kurtosis	local range
global maximum	local entropy
global minimum	
global median	
global range	

In this research, genetic operators are used as means to create temporary offspring population. Its usage is explained in Section II-D. This way, the diversity within the population is preserved throughout the evolutionary process.

D. Selection of Offspring Population

The selection operation in Section II-C is normally used in standard GA to select the next member of offspring population which will be the new population to be evaluated in the next iteration. However, in this research, the new population for the next iteration is not offspring population but a group of selected individuals from both parent and offspring populations instead. In this case, non-dominated sorting genetic algorithm II (NSGA-II) is the selection method used to select members for the new population.

NSGA-II is a selection mechanism which ensures the survival of a set of elite individuals [4]. A characteristic of multi-objective optimization is that the results are a set of solutions which cannot overwhelm each other in terms of objective values [3]. NSGA-II makes use of this concept by breeding an offspring population from the existing one. After that, offspring population and parent population are combined into one individual pool. From this individual pool, each individual will be assigned a rank based on every objective values it possess. Individuals with the same rank mean that they cannot dominate each other in every objective values. On the other hand, individuals with a lower rank means they are being dominated by the ones assigned a higher rank. A group composed of individuals with the same rank is called a front and the first front which belongs to the highest rank individuals is called the non-dominated front. Members of the next population are selected based on these fronts.

Using NSGA-II, the evolutionary process ensures the survival of elite individuals while reduces the run time compared to using standard NSGA.

E. Fitness Evaluation

Fitness value represents capability of a program in LGP in numerical format. In this research which using MOGP, the fitness value is referred to as objective value instead. The NSGA-II relies on these value to separate individuals into fronts. This way, it influence the likelihood of an individual to be selected as a member of new population and be developed further. For every objective required for measurement, every individual must possess the same number of objective values with one objective value corresponding to one objective measurement. The objectives to be optimized will be explained further in Section III.

The evaluation of an individual, which is a feature extraction program, is performed based on the assumption that a good set of features makes better classification results. Therefore, the classification results will reflect the performance of the feature extraction program as well.

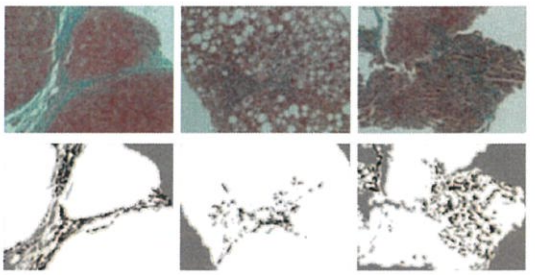


Fig. 3. Examples of the liver biopsy image (top) and its corresponding ground truth (bottom). The black, white, and gray pixels denote fibrosis tissue, normal tissue, and background, respectively.

III. EXPERIMENTAL RESULTS

A. Image Dataset

Liver biopsy image analysis in this research prioritizes on segmentation of fibrosis tissue. It can be used in medical assessment to determine the severity of damage occurred in the liver. From this step, further medical treatment plan can be decided.

To achieve the goal of this research, experiments have been conducted with a dataset of liver biopsy images used in Meejaroen et al.'s work [16]. The dataset consisted of 10 training images and 22 test images. The images were resized into 128×64 pixels. The quantity of fibrosis in an image varied from 2.36 to 22.21%.

B. Experiment Set-up

Using the proposed method, the evolutionary run was performed 10 times with the same parameter setting in Table II.

The following measures have been used to evaluate the proposed method: segmentation accuracy, precision, recall, and

TABLE II. PARAMETER SETTINGS

Parameter	Setting
Population size	100
Maximum generations	900
Selection	NSGA-II
Crossover operator	One-point crossover
Crossover rate	0.8
Mutation operator	insertion, deletion, modification
Mutation rate	0.5
Minimum program length	4 operations
Maximum program length	20 operations
Number of image registers	8
Number of numerical registers	8
Number of primitive operations	39

F-measure. They are calculated as follows:

$$\begin{aligned} Accuracy &= \frac{tp+tn}{tp+tn+fp+fn}, \\ Precision &= \frac{tp}{tp+fp}, \\ Recall &= \frac{tp}{tp+fn}, \\ F\text{-}measure &= 2 \times \frac{precision \times recall}{precision + recall}, \end{aligned} \tag{1}$$

where tp, tn, fp, and fn are true positive, true negative, false positive, and false negative pixels, respectively.

True positive (tp): a pixel is classified as fibrosis tissue pixel and the actual class of that pixel is also fibrosis tissue as well.

True negative (tn): a pixel is classified as normal tissue pixel and the actual class of that pixel is also normal tissue pixel as well. Another case of true negative is when a pixel is classified as background pixel and the actual class is also background pixel as well.

False positive (fp): a pixel is classified as fibrosis tissue pixel but the actual class of the pixel is either normal tissue or background pixel instead.

False negative (fn): a pixel is classified as normal tissue or background pixel but the actual class of the pixel is classified as fibrosis tissue pixel instead.

Moreover, the fibrosis estimation error of the proposed and compared methods were also measured. To calculate this value, percentage of fibrosis needs to be calculated first. It is a value which quantizes the percentage of fibrosis tissue area and normal tissue area from a liver tissue image. The fibrosis estimation error is the absolute difference between the percentage of fibrosis from segmented image and its respective ground truth as shown in the following equation.

$$\begin{aligned} Percentage\ of\ fibrosis\ (PoF) &= \frac{n_f}{n_f + n_t} \times 100, \\ Fibrosis\ estimation\ error &= \mid PoF_p - PoF_{gt} \mid, \end{aligned} \tag{2}$$

where n_f and n_t denote the counted fibrosis pixels and normal tissue pixels, respectively while PoF_p and PoF_{gt} denote the percentage obtained from the segmented image using proposed method and the one from its ground truth image, respectively.

C. Result and Discussion

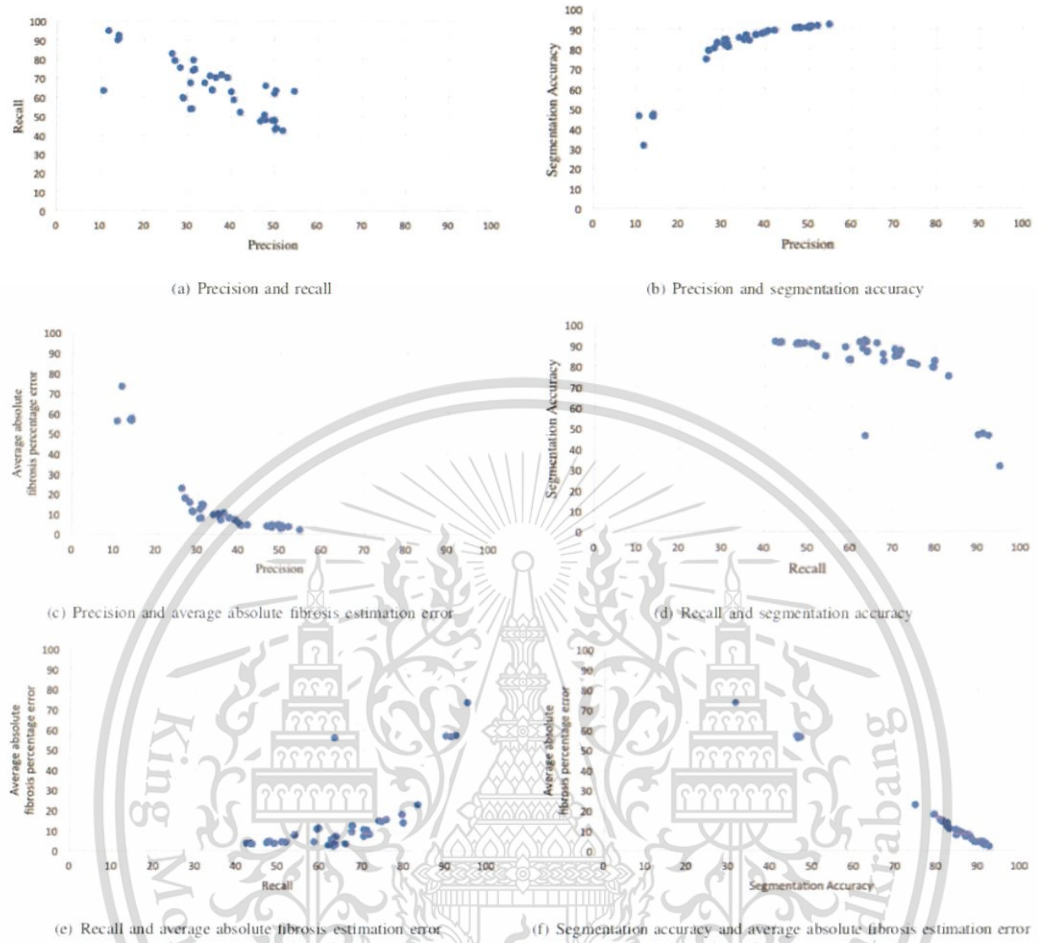
The result of the evolutionary process were individuals in the non-dominated front as shown in Fig. 4. The graphical representation of the result in Fig. 4 shows various variation of individuals with different objective values. Table III displays the selected individual from each evolutionary run. Concurrently, top-five individuals from every evolutionary run are selected based on segmentation accuracy, F-measure, and average fibrosis percentage error (Table IV). The results from both table were compared with a liver fibrosis detection method proposed by Meejaroen et al. [16] by using Bayesian classifier. Furthermore, the sample classification resulted from top-five individuals based on average fibrosis percentage error are shown in 3.

In Fig. 4, there are five different graphical representations of the non-dominated front. Each dot in a graph represents an individual position in each objective value comparison. The ideal distribution for GA with NSGA-II is a curve line whose direction depends on the type of objective optimization. The distribution shape of the comparison between maximization and maximization objective will be similar to the one in Fig.4(d). On the other hand, the distribution shape of comparison between maximization and minimization objective would normally result in the shape similar to Fig.4(c). In this case, it resembles the graphs that have y-axis as average absolute fibrosis percentage error which is minimization objective. However, the strange shape in Fig. 4(e) probably implies that recall might have a lower influence on the absolute fibrosis percentage error than the others. As recall indicates the amount of fibrosis tissue correctly classified, the fibrosis percentage also depends on the number of normal tissue pixels as well. In this case, precision and segmentation accuracy have strong influence towards minimization of average absolute fibrosis percentage error because both require false positive in consideration.

In terms of the average absolute fibrosis percentage error (referred to as fibrosis estimation error in Table III and Table IV), about half of the individual in Table III in bold format were able to achieve better result while the rest have similar range compared with Bayesian [16] method. The individual which possess lowest error (2.09) also surpasses the base method in segmentation accuracy as well. The top-five individuals in Table IV also have similar results.

Other than the absolute fibrosis percentage error, many individuals from both tables also achieved competitive result in segmentation accuracy and recall as well. On the other hand, precision and F-measure still could not surpass the base method except in Table IV. A few of individuals with precision 70.66, 69.77 and, 67.94 % which rarely occur compared to the others. For F-measure, because of the fact that it is calculated using precision and recall, a drop in either one of the two would result in a lower F-measure.

The reason that some of the individuals possess lower objective values could be explained with the nature of the fibrosis tissue which often occurs in between normal tissue. Some certain area has dark green color with high intensity of dark red color surrounding. These area might be hard to notice with naked eye without looking in detail. However, these area exists and could be considered as gray area between normal tissue and fibrosis tissue. On the other hand, the gray areas also



(a) Precision and recall

(b) Precision and segmentation accuracy

(c) Precision and average absolute fibrosis estimation error

(d) Recall and segmentation accuracy

(e) Recall and average absolute fibrosis estimation error

(f) Segmentation accuracy and average absolute fibrosis estimation error

Fig. 4. The statistical plot of the non-dominated front obtained from the fourth evolutionary run

applied to background which denoted as ocean green color. Some parts of the tissue area have small holes in between which show the background. As a result, these gray area might be neglected by being blurred through image processing filters. Perhaps the adjustment could be made by simply increasing the generation limit because the sequence of operations which can deal with the problem might not yet being found.

IV. Conclusion and Future Work

This research proposed an automatic approach to construct feature extractor in order to detect liver fibrosis tissue. The evolved feature extractor was measured and optimized in different aspects using MOGP. One of the best individual obtained through many evolutionary run possessed 2.09 fibrosis percentage error which was smaller than the compared handcraft method with the value of 2.63.

TABLE III. Performance of selected individuals from every run compared with Bayesian method

Run	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)	Fibrosis estimation error
1	**92.61**	54.72	**63.18**	58.65	**2.28**
2	91.14	48.38	**66.45**	55.99	3.34
3	**93.05**	57.85	56.57	57.20	**2.09**
4	**92.90**	57.35	54.75	56.02	**2.27**
5	**92.50**	53.95	**63.99**	58.54	**2.33**
6	91.80	50.99	**62.96**	56.34	**2.57**
7	91.49	49.98	**66.97**	57.24	3.12
8	92.12	52.32	**63.32**	57.29	2.81
9	92.12	51.62	**62.25**	56.44	**2.54**
10	**93.44**	62.39	53.58	57.65	2.77
Bayesian [16]	92.33	65.31	59.64	62.35	2.63

The advantage of the proposed method is the mass exploration of multiple solutions. While using multi-objective

TABLE IV. PERFORMANCE OF TOP-FIVE INDIVIDUALS IN THREE DIFFERENT OBJECTIVES: ACCURACY, F-MEASURE, AND FIBROSIS PERCENTAGE ERROR

Method	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)	Fibrosis estimation error
Bayesian [16]	92.33	65.31	59.64	62.35	2.63
Accuracy	**93.54**	**70.66**	40.88	51.80	4.59
	93.44	62.39	53.58	57.65	2.77
	93.42	**69.77**	56.47	47.18	4.76
	93.37	61.64	52.78	56.53	**2.61**
	93.34	**67.94**	58.51	46.87	4.54
F-measure	**92.61**	54.72	**63.18**	58.65	**2.28**
	92.50	53.95	**63.99**	58.54	**2.33**
	93.05	57.81	59.22	58.51	**2.41**
	92.02	52.50	**64.90**	58.04	2.64
	92.50	54.28	**63.04**	58.33	2.76
Fibrosis	**93.05**	57.85	56.57	57.20	**2.09**
	92.90	57.35	54.75	56.02	**2.27**
	92.61	54.72	**63.18**	58.65	**2.28**
	92.50	53.95	**63.99**	58.54	**2.33**
	93.09	58.80	54.34	56.48	**2.38**

as a mean to avoid local optima, the solutions were also automatically evaluated for fitness instead of using manual reasoning to do the same for every solution. It is also an approach to ensure the correctness of the obtained solutions in term of its performance. Each solution possess different strong and weak aspects. As a result from manual selection, the selected individuals' performance were able to reach the competitive level while some of them are better compared with the base method which is a hand-craft method. Nevertheless, as liver fibrosis detection is a problem that can affect the quality of human life, the proposed method shows promising result and can be optimized further to explore and obtain better solutions.

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fat detection

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