บันทึกข้อความ

ส่วนราชการ มหาวิทยาลัยเทคโนโลยีราชมงคลตะวันออก วิทยาเขตจักรพงษภูวนารถ โทร. ๐ ๒๖๙๒ ๒๓๖๐
ที่ อว ๐๖๕๑.๒๐๘(๑)/๑๓๖๘ **วันที่** ๒๖ สิงหาคม ๒๕๖๔
เรื่อง ขอส่งแบบอนุมัติรางวัลแก่นักวิจัยที่มีผลงานวิจัยตีพิมพ์ในวารสารวิชาการระดับชาติและระดับนานาชาติ

เรียน ประธานคณะกรรมการบริหารกองทุนส่งเสริมงานวิจัยของมหาวิทยาลัย

ด้วย คณะบริหารธุรกิจและเทคโนโลยีสารสนเทศ มหาวิทยาลัยเทคโนโลยีราชมงคลตะวันออก มีความประสงค์ขออนุมัติรางวัลแก่นักวิจัยที่มีผลงานวิจัยตีพิมพ์ในวารสาร/บทความวิชาการระดับชาติและระดับนานาชาติ รายนางอรวรรณ ชุณหปราณ ที่มีบทความวิจัยตีพิมพ์ในรายงานสืบเนื่องจากการประชุมวิชาการและเสนอผลงานวิจัยระดับชาติ JCSSE2021 “Cybernetics for Human Beings” The 18th International Joint Conference on Computer Science and Software Engineering

ในการนี้ คณะบริหารธุรกิจและเทคโนโลยีสารสนเทศ ขอนำส่งเอกสารเพื่อขออนุมัติรางวัลแก่นักวิจัยที่มีผลงานวิจัยตีพิมพ์ในวารสาร/บทความวิชาการระดับชาติ และระดับนานาชาติ ตามเอกสารที่แนบพร้อมนี้

ที่	ชื่อบทความวิจัย	ชื่อนักวิจัย
๑	การจำแนกผู้ป่วยมะเร็งเต้านมจากภาพอัลตราซาวนด์และแมมโมแกรมด้วยวิธีการเรียนรู้เชิงลึก Combination Ultarsound and Mammography for Breast Cancer Classification using Deep Learning	นางอรวรรณ ชุณหปราณ

จึงเรียนมาเพื่อโปรดพิจารณา

ละอองศรี เหนี่ยงแจ่ม

(นางสาวละอองศรี เหนี่ยงแจ่ม)
คณบดีคณะบริหารธุรกิจและเทคโนโลยีสารสนเทศ
มหาวิทยาลัยเทคโนโลยีราชมงคลตะวันออก

แบบขออนุมัติรางวัลแก่นักวิจัยที่มีผลงานวิจัยตีพิมพ์ในวารสารวิชาการ
ระดับชาติและระดับนานาชาติ

ชื่อการประชุมวิชาการ/วารสารวิชาการ____การประชุมสัมมนาทางวิชาการระดับนานาชาติ JCSSE2021 "Cybernetics for Human Beings" The 18th International Joint Conference on Computer Science and Software Engineering______

ชื่อบทความ (ไทย)____การจำแนกผู้ป่วยมะเร็งเต้านมจากภาพอัลตราซาวนด์และแมมโมแกรมด้วยวิธีการเรียนรู้เชิงลึก_______

ชื่อบทความ (อังกฤษ)_ Combination Ultrasound and Mammography for Breast Cancer Classification using Deep Learning__

ประเภทบทความ ☑ การประชุมวิชาการ วันที่จัดการประชุม ___30 June 2021 – 3 July 2021___________

นำเสนอใน session ที่ __Image Processing___ เวลา _____14.45 – 16.00 น._____วันที่ ____1 July 2021____

☐ เทคนิคการรายงานวารสารปริทัศน์

☐ วารสารวิชาการที่ปรากฏในฐานข้อมูล

☐ TCI 1 ☐ TCI 2 ☐ SCOPUS (Q1,2) ☐ SCOPUS (Q3,4) ☐ ISI

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☐ สิทธิบัตร เลขที่สิทธิบัตร___________________________

ระดับบทความ ☐ ระดับชาติ ☑ ระดับนานาชาติ

ตีพิมพ์เผยแพร่ หน้า __________ Vol. ____ No. _____ ปี พ.ศ. ________

ลำดับที่	ชื่อผู้แต่ง / ผู้ร่วมแต่ง	จำนวนเงิน (บาท)	ลายมือชื่อ
1	นางอรวรรณ ชุณหปราณ	3,000	(ลายมือชื่อ)
2	นางสาวต้องใจ แย้มผกา		ต้องใจ แย้มผกา
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ผู้ยื่นเรื่อง
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วันที่ 25 / ส.ค / 64

รองคณบดีฝ่ายวิชาการฯ
( )
วันที่ 25 / ส.ค. / 64

หัวหน้าสาขาวิชา
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หลักฐานแนบ 1. สำเนาหน้าปก และบทความที่ได้ตีพิมพ์และเผยแพร่ในการประชุม/วารสาร ฉบับสมบูรณ์
2. Proceedings การประชุม (Hard Copy และ/หรือ CD)
3. หลักฐานที่มีค่า ISI Impact Factor หรือการจัดอยู่ในควอไทล์ (กรณีเป็นวารสาร)

หมายเหตุ 1. กรณีที่มีผู้วิจัยมากกว่า 1 คน ให้ผู้ที่ยื่นขอรับรางวัล นำรางวัลไปจัดสรรในกลุ่มผู้วิจัยเอง คณะกรรมการจะไม่รับผิดชอบกรณีการจัดสรรรางวัลในกลุ่มผู้วิจัย

JCSEE-2021

ISBN: 978-1-6654-3831-5

Cybernetics For Human Beings

Virtual conference

The 18th International Joint Conference on Computer Science and Software Engineering

June 30 – July 3, 2021

Organized by Thammasat University

2021 18th International Joint Conference on Computer Science and Software Engineering (JCSSE) | 978-1-6654-3831-5/21/$31.00 ©2021 IEEE | DOI: 10.1109/JCSSE53117.2021.9493835

2021 18th International Joint Conference on Computer Science and Software Engineering (JCSSE) | 978-1-6654-3831-5/21/$31.00 ©2021 IEEE | DOI: 10.1109/JCSSE53117.2021.9493838

2021 18th International Joint Conference on Computer Science and Software Engineering (JCSSE)

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IEEE catalog number:	CFP2132P-ART
ISBN:	978-1-6654-3831-5

2021 18th International Joint Conference on Computer Science and Software Engineering (JCSSE) | 978-1-6654-3831-5/21/$31.00 ©2021 IEEE | DOI: 10.1109/JCSSE53117.2021.9493851

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Message from General Chairs

It has been almost two years since 2019 that Coronavirus disease became a severe pandemic. The end of this unexpected pandemic seems unpredictable. However, the advancement of our research in computer science must be proceeded with new working environments. Our colleagues from Thammasat University overcame various pandemic obstacles and devoted a great effort to make JCSSE 2021 a success.

There are 67 submitted papers from Pakistan, Thailand, Vietnam, Singapore, India, Australia, Japan, Korea, United Kingdom, and China. Only 39 papers were accepted, which is equal to 59% acceptance rate. JCSSE 2021 is honoured and deeply thankful to have the following distinguished professors to be our keynote speakers.

1. Professor Dr. Maomi Ueno from The university of electro-communications, Japan to talk about “AI based e-Testing as a common yardstick for measuring human abilities”.
2. Professor Dr. Siriwan Suebnukarn from Thammasat University, Thailand to talk about “Intelligent Clinical Training during the COVID-19 Pandemic”.
3. Professor Dr. Pedro Melo-Pinto from The University of Trás-os-Montes e Alto Douro, Portuguese to talk about “Towards robust Machine Learning models for grape ripeness assessment”.

Furthermore, the following experts from several organizations kindly helped us arrange the tutorial sessions, which we feel highly appreciated.

1. Dr. Prachya Boonkwan from National Electronics and Computer Technology Center (NECTEC), Thailand to lecture on “A Beginner's Tutorial on Thai NLP from Scratch with LST20 Corpus”.
2. Assistant Professor Dr. Worawan Diaz Carballo from Thammasat University, Thailand to lecture on “High Performance Computing Workshop for the Impatients”.
3. Dr. Thittaporn Ganokratanaa from Applied Computer Science Program, Dept. of Mathematics, Faculty of Science King Mongkut’s University of Technology Thonburi, Thailand to lecture on “Deep learning for computer vision applications”.

JSSE 2021 is successful because of the devoting efforts of our colleagues from Thammasat University to host and organize the conference. In addition, the hard work of conference secretaries, steering committee, organizing committee, technical committee, reviewers is greatly thankful.

I wish everyone is healthy and our daily lives are back normal soon. Let us enjoy the academic atmosphere of JCSSE 2021 and forget about COVID-19 for a while.

Chidchanok Lursinsap

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Conference Program

30-Jun-21

Time	Title	Speaker
09.00-16.00	Workshop : A Beginner's Tutorial on Thai NLP from Scratch with LST20 Corpus	Dr. Prachya Boonkwan, NECTEC
09.00-16.00	Workshop : Deep learning for computer vision applications	Dr.Thittaporn Ganokratana, KMUTT

1-Jul-21

Time	Title	
8.45-9.15	MC invite General Chair (Professor Chidchanok Lursinsap) to report	
	General Chair (Professor Chidchanok Lursinsap) reports and invite the Master of Ceremony	
	(Rector of Thammasat University: Associate Professor Gesinee Witoonchart) to Open	
	The Master of Ceremony (Rector of Thammasat University: Associate Professor Gesinee Witoonchart) Open the conference	
09.15-09.30	Take Group Photos	
09.30-10.30	Keynote Speech AI based e-Testing as a common yardstick for measuring human abilities Prof. Maomi Ueno Chair: Dr. Pokpong Songmuang, TU	
10.30-10.45	Break #1	
10.45-12.00	**Algorithms & Optimization** Chair: Assoc. Prof. Dr. Yaowadee Temtanapat (TU) and Assoc. Prof. Dr. Suphakant Phimoltares (CU) Facilitator: Taweewat Luangwiriya	**Cloud Computing** Chair: Asst. Prof. Dr. Pinyo Taeprasartsit (SU) and Asst. Prof. Dr. Worawan Diaz Carballo (TU) Facilitator: Kanyalag Phodong
10.45-11.00	COVID-19 Classification using DCNNs and Exploration Correlation using Canonical Correlation Analysis (Rujira Jullapak and Tongjai Yampaka)	Transmission Sequencing to Improve LoRaWAN Performance (Krit Wongwatthanaroek)

11.00-11.15	Maximizing the Generative Performance of Echo State Networks Using the Particle Swarm Optimization (Kristsana Seepanomwan)	Epsilon: A Microservices based distributed scheduler for Kubernetes Cluster (Alex Neo Jing Hui and Bu Sung Lee)
11.15-11.30	Quality Evaluation Method of 2D SLAM Map (Natcha Cota et.al)	Next Generation Cloud Computing: Security, Privacy and Trust Issues from the System View (Ron Bester and M Arif Khan)
11.30-11.45	Vertebrae Pose Segmentation based on Temporal Anisotropic Diffusion and Ensembled Gradient (Podchara Klinwichit et.al)	Detecting Anomaly and Replacement Prediction for Rainfall Open Data in Thailand (Intouch Prakaisak et.al)
11.45-12.00	ILM and Fovea Detection using Standard Deviation Profiling Method (Mohamed Shahud Hussain et.al)	Mobile Applications vs. Chat-based Applications: A Comparative Study based on Academic Library Domain (Watanee Jearanaiwongkul et.al)
12.00-13.30	Lunch	
13.30-14.30	Keynote Speech Towards robust Machine Learning models for grape ripeness assessment Prof. Pedro Melo-Pinto Chair: Assoc.Prof.Dr. Chutiporn Anutariya, AIT	
14.30-14.45	Break #2	
14.45-16.00	**NLP** Chairs: Dr. Prachya Boonkwan (NECTEC) and Dr. Jaruwat Pailai (KU) Facilitator: Rattapoom Kedtiwerasak	**Image Processing** Chairs: Asst.Prof.Dr.Narumol Chumueng (MCRU) and Dr. Thittaporn Ganokratanaa (KMUTT) Facilitator: Pannavich Khowrurk
14.45-15.00	Text Summarization for Thai Food Reviews using Simplified Sentiment Analysis (Paitoon Porntrakoon et.al)	Combination Ultrasound and Mammography for Breast Cancer Classification using Deep Learning (Orawan Chunhapran and Tongjai Yampaka)

15.00-15.15	Asynchronously Parallel Decoding For Automatic Speech Recognition Services (Nattapong Kurpukdee et.al)	Smart Inventory Access Monitoring System (SIAMS) using Embedded System with Face Recognition (Kanjana Eiamsaard et.al)
15.15-15.30	Classification of Abusive Thai Language Content in Social Media Using Deep Learning (Ruangsung Wanasukapunt and Suphakant Phimoltares)	Incorporating Prior Scientific Knowledge Into Deep Learning for Precipitation Nowcasting on Radar Images (Pattarapong Danpoonkij et.al)
15.30-15.45	Topic Modeling Enhancement using Word Embeddings (Siriwat Limwattana and Santitham Prom-on)	Smart School Attendance System using Face Recognition with Near Optimal Imaging (Kittipong Tapyou et.al)
15.45-16.00	Non-Functional Requirement Extraction by using Conceptual Graphs (Taweewat Luangwiriya and Rachada Kongkachandra)	Detecting Facial Images in Public with and without Masks Using VGG and FR-TSVM Models (Hangkai Wang and Chidchanok Lursinsap)

2-Jul-21

Time	Title	
09.30-10.30	Keynote Speech Intelligent Clinical Training during the COVID-19 Pandemic Prof. Siriwan Suebnukarn Chair: Assoc.Prof.Dr. Yaowadee Temtanapat, TU	
10.30-10.45	Break #1	
10.45-12.00	**Game, VR** Chairs: Asst. Prof. Dr. Narit Nhuhom (MU) and Asst. Prof. Dr. Teeradaj Racharak (JAIST) Facilitator: Taweewat Luangwiriya	**Data Science and Predictive Models** Chair: Asst. Prof. Dr. Wasit Limprasert (TU) and Dr. Marut Buranarach (NECTEC) Facilitator: Kwanrutai Saclim

10.45-11.00	Guideline of Personalized Facial Makeup Using a Hierarchical Cascade Classifier (Sasipa Panthuwadeethorn et.al)	Mass-ratio-variance based Outlier Factor (Phichapop Changsakul et.al)
11.00-11.15	SEPBO: Trash separator bot VR game (Thirada Theethum et.al)	Performance Measurement of Federated Learning on Imbalanced Data (Pramote Sittijuk)
11.15-11.30	Musical Pitch Alphabets Generator using Haar-like Feature (Kiratijuta Bhumichitr et.al)	Ontology for Blood Group Phenotyping and ABO Discrepancy Screening (Areerat Trongratsameethong et.al)
11.30-11.45	A Development of Game-Based Learning in Virtual Reality for Fire Safety Training in Thailand (Kodchaporn Satapanasatien et.al)	Evolving Compact Prediction Model for PM2.5 level of Chiang Mai using Multiobjective Multigene Symbolic Regression (Prakarn Unachak and Prayat Puangjaktha)
11.45-12.00	Location-based Daily Human Activity Recognition using Hybrid Deep Learning Network (Sakorn Mekruksavanich et.al)	Predicting Football Match Result Using Fusion-based Classification Models (Chananyu Pipatchatchawal and Suphakant Phimoltares)
12.00-13.30	Lunch	
13.30-14.45	**Machine Learning** Chairs: Asst. Prof. Dr. Teeradaj Racharak (JAIST) and Dr. Sarun Gulyanon (TU) Facilitator: Pannavich Khowrurk	**IoT and Cybernetics** Chair: Dr. Konlakorn Wongpatikaseree (MU) and Dr. Nattapon Kumyaito (NU) Facilitator: Rattapoom Kedtiwerasak
13.30-13.45	Hybrid Input-type Recurrent Neural Network Language Modeling for End-to-end Speech Recognition (Phuttapong Sertsi et.al)	Performance Analysis in UAV-enabled Relay with NOMA under Nakagami-m Fading Considering Adaptive Power Splitting (Nguyen Nhat et.al)

13.45-14.00	Implementing Machine Learning Methods for Ballpoint Pen Ink Classification based on Mass Spectrometry Data: Toward a Forensic Application (Pirada Boonna et.al)	Physical Layer Security in Cognitive Radio Networks for IoT Using UAV With Reconfigurable Intelligent Surfaces (Vo Van et.al)
14.00-14.15	Classification of Astronomical Objects in the Galaxy M81 using Machine Learning Techniques II. An Application of Clustering in Data Pre-processing (Tapanapong Chuntama et.al)	IoT System Design For Agro-Tourism (Thittaporn Ganokratanaa et.al)
14.15-14.30	Identification of Discriminative Features from Light Curves for Automatic Classification of Variable Stars (Prapaporn Techa-Angkoon et.al)	Deep Index Price Forecasting in Steel Industry (Thittaporn Ganokratanaa and Mahasak Ketcham)
14.30-14.45		Rapid Deployment of Ultra-Wideband Indoor Positioning System (Phatham Loahavilai et.al)
14.45-15.30	Closing Ceremany	

Combination Ultrasound and Mammography for Breast Cancer Classification using Deep Learning

2021 18th International Joint Conference on Computer Science and Software Engineering (JCSSE) | 978-1-6654-3831-5/21/$31.00 ©2021 IEEE | DOI: 10.1109/JCSSE53117.2021.9493840

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Abstract— **The most widely used methods for early detection of breast cancer are Ultrasound and Mammography. However, single ultrasound or single mammography shows false classification that causes unnecessary biopsy. Therefore, the combination approach is proposed to improve breast cancer classification using the deep learning technique. The proposed method has been divided into two steps. First, images are randomly combined using the k-combination method. Second, deep learning based on MobileNet is used to classify breast tumors. The result demonstrated that the combination approach produces a variety of patterns and a large image dataset and improves the accuracy. In addition, the false positive tend to reduce by 13% and the false negative tend to reduce by 14%. It is useful to avoid unnecessary surgery and to plan aggressive treatment.**

Keywords— breast cancer classification; combination imae; breast ultrasound; breast mammography

I. Introduction

Breast cancer is the leading cause of death for women. Early screening and diagnosis have been reduced the death rate. Therefore, the screening method requires accurate and reliable tools to distinguish benign and malignant tumors. Breast ultrasound and Mammography are routine screening methods. Nevertheless, single ultrasound or single mammography are not perfect tools because some tumors are missed particularly in dense breast [1], or distinguishes between fat tissues, hematoma, fibroadenolipoma, lactating adenomas, or cyst. Although computer-aided diagnosis in mammography is more improved, supplemental ultrasound is also used for the second look or follows up the result when the suspicious mammography is found. Many studies reported that a combination of mammography and breast ultrasound more efficiently detected breast cancer than single mammography [2, 3, 4, 5, 6]. In addition, these studies demonstrated that the high accuracy, low false-positive (FP) rate, and false-negative (FN) rate were reduced by using the combination method.

In the last decade, Computer Aid Diagnosis (CAD) has been developed for breast cancer detection and classification to improve sensitivity and specificity [7]. Many techniques such as linear discriminant analysis (LDA), support vector machine (SVM) and artificial neural network (ANN) [8, 9, 10] have been proposed for breast lesions detection and classification. In recent years, deep learning is popularly used to analyze the medical images. The interesting survey [11] reviewed over 300 contributions and reported effective medical image analysis using a deep learning approach. The major challenge is designing such systems to extract of features from the images by computer instead of a human. The many studies in the medical image using deep learning is rapidly growing every year [12, 13, 14]. These studies showed that the convolutional neural networks (CNNs) technique is effectively used to extract the image features, especially in breast cancer classification. However, according to these surveys, the combination of ultrasound and mammography images was not available.

This study aims to combine ultrasound and mammography images for breast cancer classification using deep learning based on MobileNet architecture. The proposed method focuses to improve the performance of breast cancer classification when compared with single ultrasound and single mammography.

II. Related Work

A. *Breast cancer screening*

The first breast cancer screening is self-examination or physical examination. When an abnormal breast is discovered by physical examination, it is usually 80% benign in cases. The physical examination performance is efficient screening. However, no studies prove physical examination has reduced mortality rates from breast cancer because only 28% of the cancer was detected. The other screening is breast ultrasound that used for the second look or follows up the result when the suspicious mammography is found. Breast ultrasound is useful in very small lesions and hard to find from mammography. Previous research [15] concluded that cancers detected in ultrasound were similar in size and stage to detect in mammography and would improve survival rate. Although breast ultrasound is not part of the National Comprehensive Cancer Network (NCCN) or the American Cancer Society (ACS) for the first screening, early detected breast mass from ultrasound screening could reduce the mortality rate [16, 17, 18, 19]. The women in average to high-risk breast cancer assessment was recommended to exam the mammography. However, some studies discussed the sensitivity as low as 30-50% [20] because mammography false classification in small mass, dense breast, hematoma, or fibroademolipoma. Therefore, ultrasound supplemental mammography has been used for the women that has dense breast and has suspicious mass in mammography. Adjunctive ultrasound screening tests may detect cancer in approximately 47% of dense breasts [21]. The effective supplemental ultrasound was reported in previous studies [22, 23, 24]. These findings found that supplemental ultrasound increased the detection rate of the node-negative invasive dense breasts. The evidence from prior studies [25, 26, 27] reported that a combination of ultrasound and mammography might still identify the vast majority of cancer when they are node-negative.

B. *Screening Performance*

The breast image interpretation is depending on the skill and experience of the radiologist. Performance comparison in sensitivity, specificity, or overall accuracy were reported in 75.3%, 96.8%, and 96.6% in single ultrasound; 77.6%, 98.8%, and 98.6% in single mammogram; and higher sensitivity 97% in combination of ultrasound and mammography [15]. Other report [2] showed 52%, and 84% in single mammogram; and 76%, and 91% in combination. Although these finding reported that ultrasound supplemental with mammography could increase cancer detection and improve performance, false positive and false negative also appeared. It leads to extra unnecessary exams and unnecessary biopsy.

C. *Improved Breast Image Analysis using Deep Learning*

Even well-trained experts may have high human errors; therefore, Computer Aid Diagnosis (CAD) has been developed for breast cancer detection and classification. Few studies in single ultrasound [28, 29, 30] demonstrated that the efficient CAD in ultrasound with improving accuracy and reducing the number of unnecessary biopsy are performed in CAD. Deep learning is the efficient technique to analyze medical image. The comparison study [31] shows performance in GD, GDM, and AGD algorithms are 76.9%, 46.2%, and 84.6% accuracies. Their concluded that AGD achieves high accuracy but suffer from time complexity. Convolutional neural network (CNNs) is popularly used in deep learning. The models are compared [32] in LeNet, U-Net, and FCN-AlexNet when combining two ultrasound modes. The results showed the true positive fraction (TPF) in 0.89, 0.91, and 0.98 respectively, but they concluded that the training dataset was insufficient. Unsupervised learning based on a neural network classifier [33] was proposed to solve the low resolution and low contrast ultrasound image. It showed 95.86% accuracy.
Deep polynomial network [34] was applied to extract the global texture feature and improved 92.40% accuracy. Although the automated detection and classification in mammography have been improved, some limitations also present in mammography. Mass detection algorithms have proposed prior to classification [35, 36]. These studies reported the effective reduction of false-positive regions and high true positive prediction. learned feature hierarchy method was proposed to segmentation using deep learning instead of handcrafted feature from mammography image [37]. They demonstrated that the deep learned feature strong positive than manual. Combing CNN and SVM proposed in [38] achieved 98.44% compared with the baseline (ConvNets). Integrated methodology for detecting, segmenting, and classifying breast mass [39] achieved 98% sensitivity and 70% specificity. In other studies, two mammogram datasets were compared [40]. The results showed 100% accuracy for training, while the testing showed only 87% accuracy. A well-known fully complex-valued relaxation network was proposed [41]. It significantly improved the performance in 99% accuracy, 98% sensitivity, and 100% specificity.

III. MATERIAL AND METHOD

A. *Material*

The datasets consist of 381 breast ultrasound and 316 mammography images. The ultrasound images are provided by Biomedical Engineering Unit of Sirindhorn International Institute of Technology, Thailand [42]. The mammography images available on MIAS Mini Mammographic Database [43].

B. *Method*

The proposed method was divided into three steps: First, images were combined and randomly selected using the k-combination method. Second, deep learning based on MobileNet was used to extract the image features. Finally, the breast mass was classified by softmax layer.

1) Combination using the k-combination and randomly selection method

Most of the time, data related issues are the main reason why machine learning cannot be accomplished. Because of the images of the same person were not available, therefore, this study proposed combination method. However, the images were combined in the same class. It means that benign ultrasound images were combined with only benign mammography images. In this step, ultrasound and mammography images were prepared. First, each image was contained in their class folder (Benign and Malignant). Second, the image numbers were defined and used to combine in the same class. Third, all pair images were resized in 320×270 pixels. In mathematics, a combination is a selection of items from a collection, such that the order of selection does not matter. For example, given three objects, say an object 1, an object 2 and an object 3, there are three combinations of two that can be drawn from this set: an object 1 and object 2; an object 1 and object 3; or an object 2 and an object 3 and so on. More formally, a k-combination of a set S is a subset of k distinct elements of S.

In experiment, The datasets consist of 381 breast ultrasound and 316 mammography images. Then, the combination images consist of 6,144 benign and 9,620 malignant. The combination using k-combinations method shows in "fig 1". The dataset was divided into 90% for training and 10% for testing by random selection. Table I shows the number of training and testing dataset.

TABLE I. THE SIZE OF TRAINING AND TESTING

Dataset	Total	Training	Testing
Single US	381	250	131
Single Mammography	316	194	22
Combination image	15,764	14,187	1,577

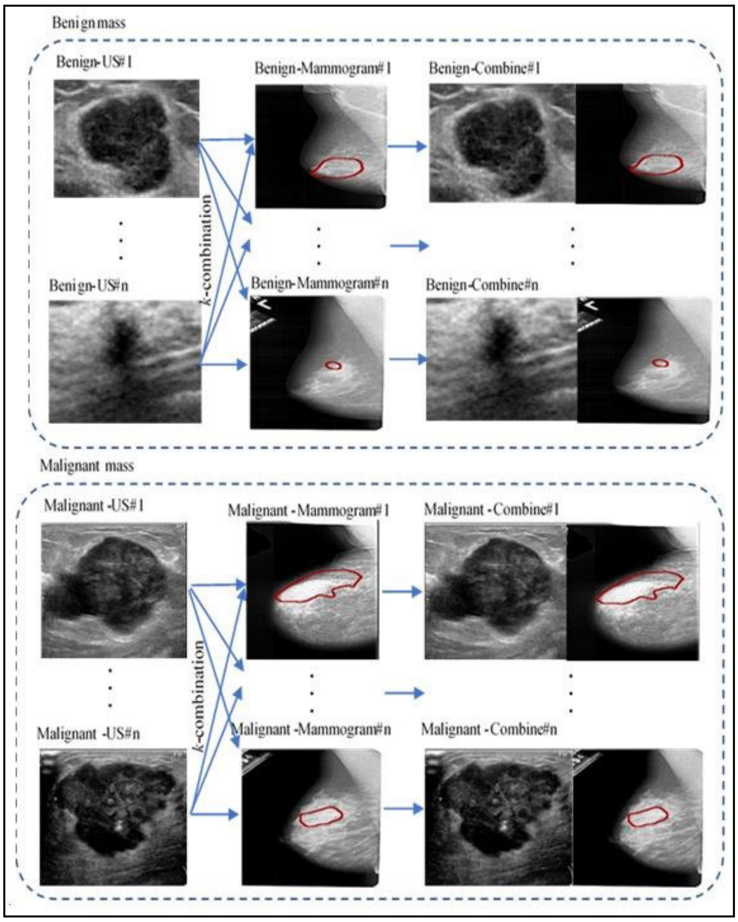
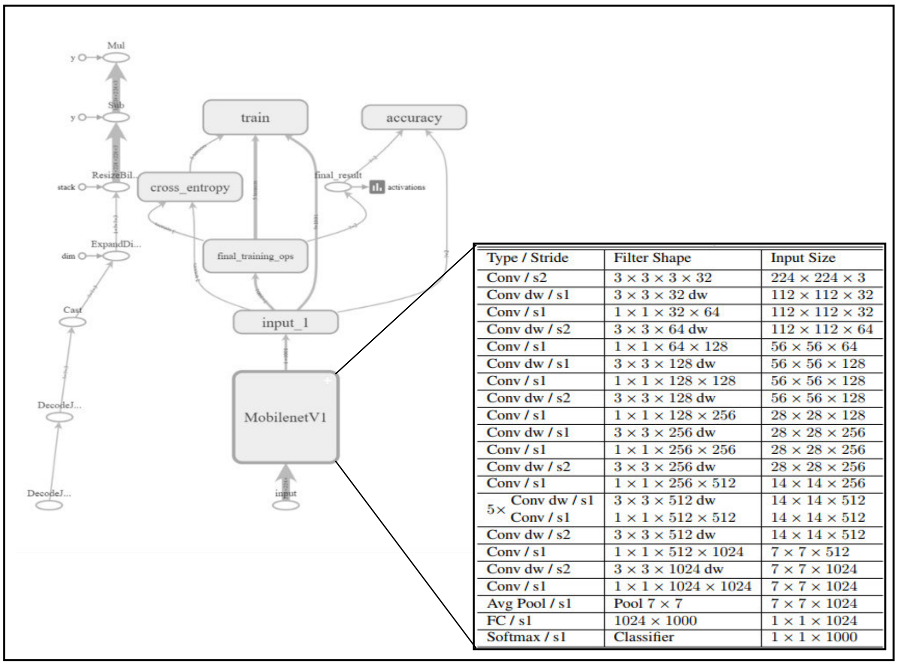


Figure 1 The combination using k-combinations method



Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
5× Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
5× Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Figure 2 MobileNet architecture

2) Deep MobileNet architecture

Deep learning in a medical image has progressed in recent years. Many techniques have become more powerful and higher accuracy. To achieve higher accuracies, complex network, large model size, and many times to training are necessary [14].

MobileNet architecture, which is very small and low latency models, was used because the retrain technique based on transfer learning is faster than the fully training model. Figure 2 shows the MobileNet architecture. All layers are followed by a batch-norm and ReLU. The final layer is fully connected layer. Softmax layer is the classification layer. The re-trained MobileNet model removes the old top layer, then, new dataset has been trained to classify the target class. Those predictions are then compared against the actual labels to update the final layer's weights through the back-propagation process.

3) Breast Cancer classification

In the practical experiment, our methodology is able to improve correctly classify the breast cancer lesions in benign or malignant using combined ultrasound and mammography image. The new random images were created and used to evaluate the prediction performance using confusion matrix that represents the correctly classified instances and report in overall accuracy, specificity, and sensitivity. In the practical experiment, our method is able to improve the breast cancer classification. The confusion matrix was used to evaluate the model performance in overall accuracy, specificity, and sensitivity.

IV. RESULT

A. Image Combination

The problem of data scarcity is very important since data are at the core of any machine learning. The combination method produces the augmented images (6,144 benign and 9,620 malignant). The size of dataset is often responsible for poor performances. The combination method is useful to improve performance and outcomes of machine learning models by forming new and different examples to train datasets. If dataset in a machine learning model is rich and sufficient, the model performs better and more accurate.

B. Classification performance

In this experiment, proposed method was compared with single ultrasound and mammography. The dataset was divided into 90% training and 10% testing. The model architecture is very small, low latency, and high accuracy. The significant problems in breast cancer diagnosis are false negative and false positive. The false negative affects with the patients who lose the chance to early treatment. The false positive prediction develops unnecessary surgery such as biopsy. Table II shows the model performance.

The results demonstrate that ultrasound shows a high specificity of 98.15%, while shows low sensitivity of 96.43%. The false negative is 3.57%, and the false positive is 1.85%. The mammography shows low specificity of 88.24%, while show a high sensitivity of 89.80%. The false negative is 10.2%, and the false positive is 11.76%. The combination method improves 100% accuracy and reduces all false predictions. This approach reduces about 14% false negative. In addition, the false positive is reduced about 13%. It means that 13% of patients could avoid unnecessary surgery such as biopsy.

TABLE II. CLASSIFICATION PERFORMANCE

	Accuracy	Sensitivity	Specificity
Ultrasound	97.27	96.43	98.15
Mammography	89	89.80	88.24
Combine	100	100	100

V. DISCUSSION

A. Combined image approach

The breast image interpretation is depending on the skill and experience of the radiologist. Even well-trained experts may have high human errors; therefore, computer-aided diagnosis (CAD) is performed to help the radiologists in breast cancer detection and classification. The variety pattern and large image dataset can be successful to learn all possible patterns, but a common problem in the medical images is the insufficient training dataset. Combination image approach could solve insufficient training dataset because it produces variety pair of images.

B. Deep Learning base on MobileNet

Deep learning technique is popular used in breast cancer classification. According to our surveys, no previous studies proposed a combination of ultrasound and mammography. Therefore, only single ultrasound and single mammography could be compared. Many studies in breast cancer classification, convolutional neural network (CNN) was used. It is time consuming. Our experiment used deep learning based on MobileNet that runs quickly with high accuracy in a limited environment device, limited computation power, and limited space.

C. Apply in Breast Cancer Prediction

Early screening and diagnosis have been reduced the death rate. Therefore, the screening method requires accurate and reliable tools to distinguish benign and malignant tumors. The significant problems, the false-negative affected with the patients who lose the chance to early treatment. The false-positive develops unnecessary surgery such as biopsy. The combination approach reduces 13% false positive which avoids unnecessary surgery and reduces false negative by 14% which immediately curable and plans for less aggressive treatment. In experiments, the combination approach tends to more efficient in breast cancer screening.

VI. CONCLUSION

The combination image approach with deep learning for breast cancer classification achieves high accuracy and reduces false prediction. The results demonstrate that combining ultrasound and mammography images is more efficient in breast cancer screening. In future work, other images related to breast cancer such as the pathological image from the biopsy are interesting to combine for modeling.

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บันทึกข้อความ

ส่วนราชการ สาขาวิชาวิทยาการคอมพิวเตอร์ คณะบริหารธุรกิจและเทคโนโลยีสารสนเทศ โทร. ๔๐๖

ที่ อว.๐๖๕๑.๒๐๘(๙)/๐๙๕ **วันที่** ๒๕ สิงหาคม ๒๕๖๔

เรื่อง ขออนุมัติรางวัลแก่นักวิจัยที่มีผลงานวิจัยตีพิมพ์ในการประชุมวิชาการระดับนานาชาติ

เรียน คณบดีคณะบริหารธุรกิจและเทคโนโลยีสารสนเทศ ผ่านรองคณบดีฝ่ายวิชาการและวิจัย และผ่านหัวหน้าสาขาวิชาวิทยาการคอมพิวเตอร์

เอกสารแนบ ๑. แบบขออนุมัติรางวัลแก่นักวิจัยที่มีผลงานวิจัยตีพิมพ์ในวารสารวิชาการระดับชาติและระดับนานาชาติ

๒. บทความวิจัยจำนวน ๑ บทความ เรื่อง Combination Ultrasound and Mammography for Breast Cancer Classification using Deep Learning

เนื่องด้วยข้าพเจ้า นางอรวรรณ ชุณหปราณ อาจารย์ประจำสาขาวิชาวิทยาการคอมพิวเตอร์ ได้เข้าร่วมการประชุมสัมมนาทางวิชาการระดับนานาชาติ เพื่อนำเสนอบทความวิจัย ในงานการประชุมสัมมนาทางวิชาการระดับนานาชาติ JCSSE2021 "Cybernetics for Human Beings" The 18th International Joint Conference on Computer Science and Software Engineering” เมื่อวันที่ ๓๐ มิถุนายน – ๒ กรกฎาคม ๒๕๖๔ ด้วยแบบระบบออนไลน์ ผ่านสื่ออิเล็กทรอนิกส์ (Zoom Meeting) โดย มหาวิทยาลัยธรรมศาสตร์ จำนวน ๑ บทความ ชื่อเรื่อง Combination Ultrasound and Mammography for Breast Cancer Classification using Deep Learning แล้วนั้น

จึงมีความประสงค์ขออนุมัติรางวัลแก่นักวิจัยที่มีผลงานวิจัยตีพิมพ์ในรายงานสืบเนื่องการประชุมวิชาการระดับนานาชาติ โดยมีแบบขออนุมัติรางวัลแก่นักวิจัยที่มีผลงานวิจัยตีพิมพ์ในรายงานสืบเนื่องการประชุมวิชาการระดับนานาชาติตามรายละเอียดข้างต้นแนบท้ายมาด้วย

จึงเรียนมาเพื่อโปรดพิจารณาอนุมัติ

ผู้ขออนุมัติ

(นางอรวรรณ ชุณหปราณ)
อาจารย์ประจำสาขาวิชาวิทยาการคอมพิวเตอร์

เรียน รองคณบดีฝ่ายวิชาการและวิจัย
เพื่อโปรดพิจารณาขออนุมัติรางวัลแก่นักวิจัยที่มีผลงานวิจัยตีพิมพ์ ในวารสารวิชาการระดับชาติและระดับนานาชาติ บทความวิจัยจำนวน ๑ บทความ เรื่อง Combination Ultrasound and Mammography for Breast Cancer Classification using Deep Learning รายนางอรวรรณ ชุณหปราณ

ดวงใจ หนูเล็ก
(หัวหน้าสาขาวิชาวิทยาการคอมพิวเตอร์)