Cancer Detection

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Abstract

Cancer is considered to be one of the most common diseases that has recently spreaded among the societies. Some cancer types are still manually recognized by doctors which definitely leads to misleading treatments. Thus there has to be a system that can automatically detect tumors and predict future cancer possibilities. We introduce a system that can detect cancerous cells in brain and lung using MRI and CT scan respectively and can also predict breast cancer probability through dense breast analysis using Mammogram images and calculating the cancer area and degree. Our system is designed to be a framework that can perform image segmentation on real data images and. The business owner will be provided with an interface that handles the outcome of segmentation process.

1 Introduction

1.1 Background

Cancer is term for diseases in which abnormal cells reproduce without control and can invade nearby tissues [1]. According to statistics [2] early diagnosis can increase the survival rate. It is shown that many people still do not know they are ill until it is too late. Our project aims to focus on detection of cancer in lung and brain and prediction of breast cancer through dense breast analysis. Our system aims to find solution for early detection of breast cancer through breast density mammogram and accurate detection which can decrease rate of misdiagnoses or surgery involvement.

1.2 Motivation

This project presents a solution for Lung/Brain cancer detection and predection of breast cancer through breast dense percentage. We have calculated the percentage of people who faced a cancer patient with (50.7 percent) and breast cancer almost took half of survey results. (51.9 percent) has faced difficulties while having their cancer tests and (30.8 percent) had inefficient results

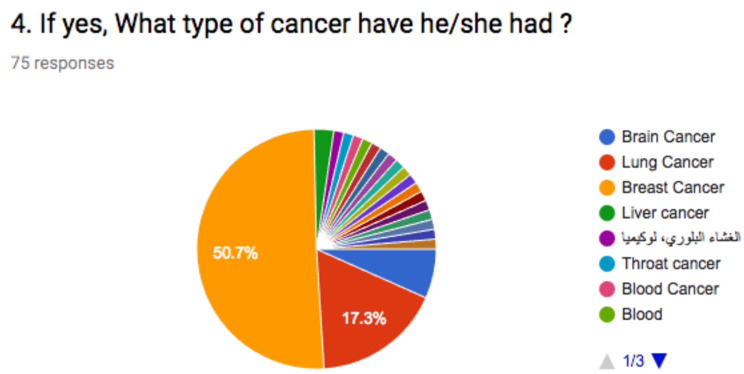


Figure 1: Survey question

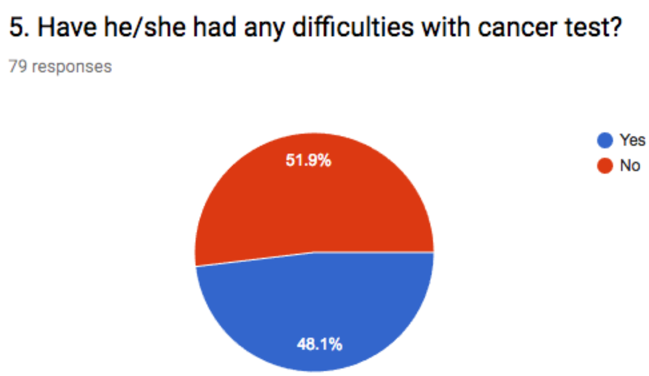


Figure 2: Survey question

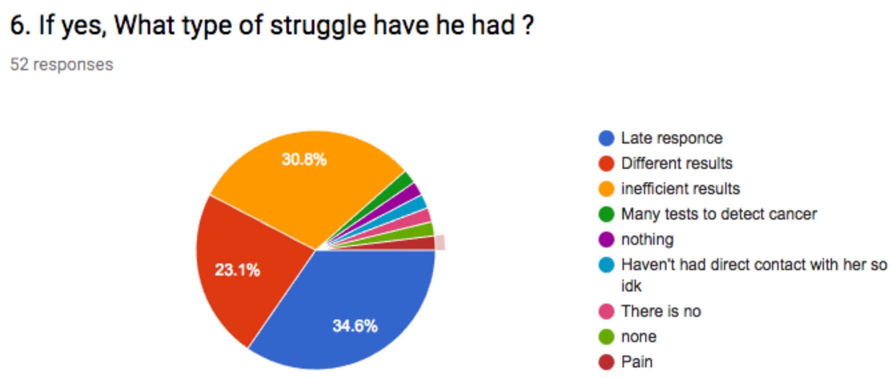


Figure 3: Survey question

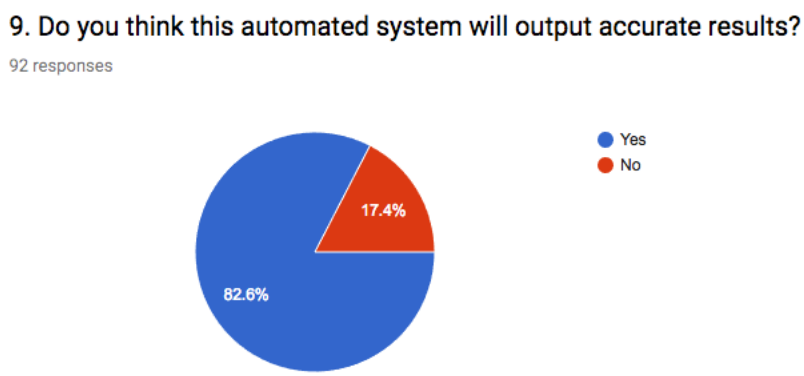


Figure 4: Survey question

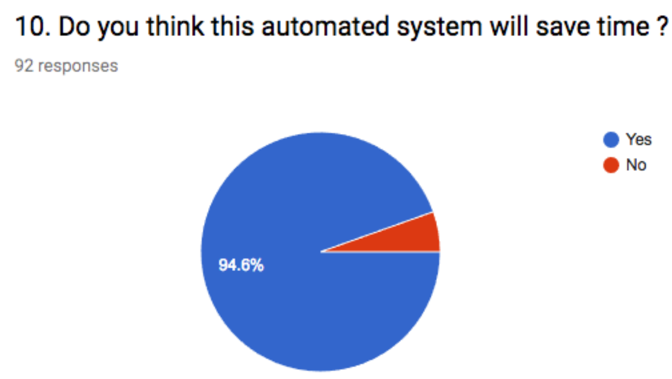


Figure 5: Survey question

•Statistics shows that Breast cancer is one of the most common cancers in Egypt. It also shows that around 50 percent of survey participants knew cancer patients who faced difficulties in diagnosis. Around 30 percent of cancer patients were facing inefficient results. and finally around 82 percent of survey participants voted that the automated system will output accurate results.

1.3 Problem Definitions

There are several problems that this project aims to solve, such as late diagnoses of cancer, and low accuracy as the images are diagnosed manually which varies from doctor to another and time consuming detection. This system aims to detect two types of cancer which are brain and lung cancers and to classify breast density into categories which may predict early breast cancer.

2 Project Description

Detecting cancerous abnormal behaviour with metric percentage for lung and brain cancers and prediction percentage of breast cancer.

2.1 Objective

Our system offers a solution to prevent late detection of cancer and to provide a new method of prediction using image processing techniques. The system also provide business owner with an accurate output. There is a subset of glioma known as glioblastoma according to [14] and there are four types of dense breast which are predominantly fat , fat with some fibroglandular tissue, heterogeneously dense and extremely dense according to [7]. Our system classifies these types by using CNN, SVM

2.2 Scope

- Business owner can view patient images.
- Business owner can view identified cancerous cells for every patient.
- Business owner can view results of prediction for dense breast.
- System can analyze images and generate statistics.
- System can boarder the tumor part.
- System can predict breast cancer possibility.

2.3 Project Overview

Our project aims to read three different types of image which are breast, lung and cancer. First step to be applied Is to import and image using interface after image is shown, Preprocessing phase starts using bias filed distortion and Normalization step and extra filters such as grayscale, gaussian and harbat... Then the segmentation step is performed to outline the tumor areas - size and location of the tumor - using K-means segmentation. Every patch should be indicating some feature such as detection if it is cancerous or not. Several features then extracted from previous work such as segmented tumor . CNN classification should be applied then on final output in order to maintain for example, type of tumor affected or Not in order to start learning also if that was image was a testing image. Accuracy and related data to that picture may be available. Finally image is showed through an interface also.

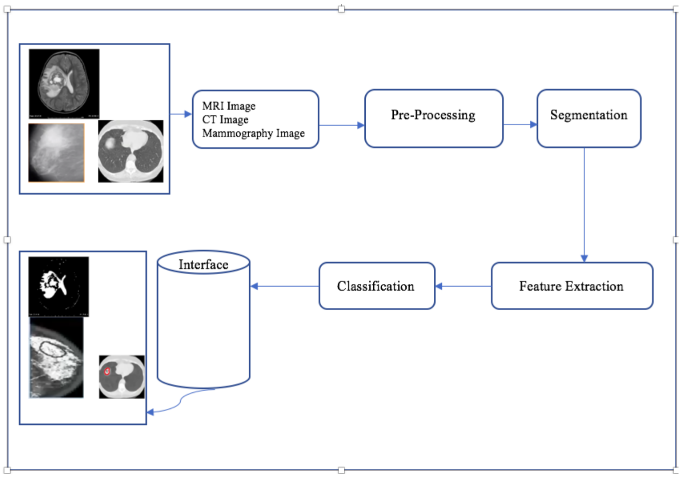


Figure 6: System Overview

3 Similar Systems

lung cancer represents a major health problem. World-wide, lung cancer is responsible for 1.3 million deaths annually. The increased amount of image data to be analyzed represents a burden for physicians. They present in [24] a new fully automated approach for segmentation of lungs with such high-density pathologies.Their method consists of two main processing steps. First, a novel robust active shape model (RASM) matching method is utilized to roughly segment the outline of the lungs. Second, an optimal surface finding approach is utilized to further adapt the initial segmentation result to the lung. Left and right lungs are segmented individually. Results showed that Their methods delivered statistically significant better segmentation results with an overall average processing time of 6 min per data set.

4-D-computed tomography (4DCT) is a challenging scale of data volume to process and analyze. Manual analysis using existing 3-D tools is unable to keep up with vastly increased 4-D data volume, automated processing and analysis are thus needed to process 4DCT data effectively and efficiently. In this paper [8], we applied ideas and algorithms from image/signal processing, computer vision, and machine learning to 4DCT lung data. Their algorithms consistently deliver desirably accurate results with high efficiency in a consistent manner: while the numeric results by the algorithms are statistically similar to those by human experts, the algorithms generates these results faster in time by at least one order of magnitudes, in 4DCT lung segmentation The time for segmenting a 4DCT lung volume took about 30 minutes using a clinical semi-automatic tool, whereas the automatic segmentation of a 4DCT took 35. minutes. Comparisons of our results with an established treatment planning system and calculation by experts demonstrated negligible discrepancies (within 2) for volume assessment but one to two orders of magnitude performance enhancement.They actively working on more features such as surface imaging manipulations, motion registration for better tracking, and the establishment of internal-external relationship. Three Machine Learners used : Naïve Bayes (NB), support vector machine (SVM), random forest (RF)

Glioma is the most common family of brain tumors, with a subset of glioma known as glioblastoma forming the most common and some of the highest-mortality and economically costly forms of brain cancer. According to this problem, the labor-intensive nature of the manual segmentation process and mistakes or disagreement between manual segmentations through images of brain. there exists a need for a fast and robust automated segmentation algorithm. Convolutional neural networks (CNNs) have been shown to be extremely effective for a variety of visual recognition and semantic segmentation tasks. In [14] they propose three novel architectures for brain tumor segmentation from multimodal MRI: a baseline voxel-wise CNN(BCN), a fully convolutional patch-wise CNN, and a full-image fully convolutional CNN with high Dice score 0.84 for BCN which is the best as FCN also and qualitatively provides very strong segmentation results than others and that also is enhanced using Dropout + Batch Normalization with average dice score 84.5 for BCN and 86.1 for FCN. Features used in these process were Gabor wavlets under the use of CNN classifier with accuracy of 0.86 Dice score , also voxel wise probabilites feature under the use of baseline convolutional network (BCN) with accuracy of 0.84 Dice score. They have used MICCAI BraTS Challenge dataset 2017 which contains T1, T1 contrast enhanced, T2, and FLAIR images for a total of 243 patients (135 glioblastoma and 108 lower grade glioma) which contains segmentations for necrotic core tumor, enhancing core tumor, nonenhancing core tumor, and edema regions. The full BraTS Challenge is to obtain the highest possible segmentation score for all four regions The images in the BraTS dataset have a consistent shape of 240 * 240 * 155 voxels.

Gliomas are the brain tumors with the highest mortality rate and prevalence. These neoplasms can be graded into Low Grade Gliomas (LGG) and High Grade Gliomas (HGG), with the former being less aggressive and infiltrative than the latter. Even under treatment, patients do not survive on average more than 14 months after diagnosis. Also, MRI images may present some problems, such as intensity inhomogeneity, or different intensity ranges among the same sequences and acquisition scanners. There are three main stages: pre-processing, classification via CNN and post-processing. Pre-Processing they applied the N4ITK method and the intensity normalization method proposed by Nyúl et al. on each sequence. CNN steps made Initialization, Activation Function, Pooling, Regularization, Data Augmentation, Loss Function, Architecture and training. In [27] they approached brain tumor segmentation as a multi-class classification problem with 5 classes (normal tissue, necrosis, edema, non-enhancing, and enhancing tumor). They evaluated the proposed method in BRATS 2013 and 2015 databases. Concerning 2013 database, they were ranked in the first position by the online evaluation platform. Features mentioned were encoding context, first-order and fractals-based texture, gradients, brain symmetry and physical properties under the use of CNN classifier based on SVM. Obtaining simultaneously the first position for the complete, core, and enhancing regions in Dice Similarity Coefficient metric (0.88, 0.83, 0.77) for the Challenge data set e also participated in the on-site BRATS 2015 Challenge using the same model, obtaining the second place, with Dice Similarity Coefficient metric of 0.78, 0.65, and 0.75 for the complete, core, and enhancing regions, respectively.

Breast density measurement is an important aspect in breast cancer diagnosis as dense tissue has been related to the risk of breast cancer development. The purpose of this study is to develop a method to automatically compute breast density in breast MRI. In this paper [5] Three preprocessing algorithms are initially applied: first, image inhomogeneities are corrected using the N3 bias field correction algorithm [25] to correct signal intensity variations within the same structure of one specific case. The N3 is a nonparametric method which was designed to be applied on early stages of automated data analysis. Second, the sternum is detected, which is used as an important landmark in different parts of our algorithm. Third, intensities of the MR images are normalized to compensate for interpatient signal intensity variability. They implemented a first-derivative based filter to enhance this edge and detect the sternum landmark and the output of the filter is binarized by an adaptive threshold set to max. The background is excluded using Otsu thresholding [18]. The STAPLE algorithm fuses a collection of manual segmentations maximizing the accuracy.Also The breast-body surface is determined by segmenting body using atlas-based voxel classification algorithm. Dice similarity coefficient (DSC), total overlap, false negative fraction (FNF), and false positive fraction (FPF) are used to report similarity between automatic and manual segmentations. For breast segmentation, These techniques were applied on a dataset of 50 cases. The proposed approach obtained DSC, total overlap, FNF, and FPF values of 0.94, 0.96, 0.04, and 0.07, respectively. The method is relevant for researchers investigating breast density as a risk factor for breast cancer and all the described steps can be also applied in computer aided diagnosis systems. signal intensity variability is initially corrected.

Breast cancer is the most prevalent cancer and the second highest cause of cancer death in women in the United States [21] so they aim in [4] to identify a new clinical marker based on quantitative kinetic image features analysis and assess its feasibility to predict tumor response to neoadjuvant chemotherapy.The authors then applied and tested two approaches to classify between CR (Complete Response) and NR (Nonresponce) cases to chemotherapy. The first one analyzed each individual feature and applied a simple feature fusion method that combines classification results from multiple features. The second approach tested an attribute selected classifier that integrates an artificial neural network (ANN) with a wrapper subset evaluator, which was optimized using a leave-one-case-out validation method. A total of 39 features were computed, which is divided into five groups. These groups include image features computed from (1) the entire tumor area, (2) the active contrast-enhanced tumor area, (3) the tumor necrotic area, (4) the entire background parenchymal region of two breasts, and (5) the absolute value of bilateral BPE(background parenchymal enhancement) feature difference computed from the left and right breasts. Some of the features are Volume, average intensity, maximum pixel intensity, standard deviation, and skewness of tumor pixel intensity, maximum value of tumor radius, and shape factor, ratio of necrotic volume over tumor volume. They also applied a well-examined synthetic minority oversampling technique called SMOTE to add a set of synthetic data in the CR case group to generate a more balanced training dataset of two class cases. Their results in the pool of 39 features, 10 yielded relatively higher classification performance with the areas under receiver operating characteristic curves (AUCs) ranging from 0.61 to 0.78 to classify between CR and NR cases. Using a feature fusion method, the maximum AUC=0.850.05. Using the ANN-based classifier, AUC value significantly increased to 0.960.03 (p ¡ 0.01). They used a dataset of 68 cancer patients before undergoing neoadjuvant chemotherapy.

Non small cell lung cancer is a prevalent disease. It is diagnosed and treated with the help of computed tomography (CT) scans. In this paper [22], they apply radiomics to select 3-D features from CT images of the lung toward providing prognostic information. Focusing on cases of the adenocarcinoma nonsmall cell lung cancer tumor subtype from a larger data set, the focus is on extracting features that can be used to predict whether patient survival time will be long or short. The initial CT segmentation, separating the lung region from the rest of the body, was done using the algorithm provided in the Lung Tumor Analysis (LuTA) software suite of Definiens. They show that classifiers can be built to predict survival time, The best accuracy when predicting survival was 77.5 percent using a decision tree in a leave-one-out cross validation and was obtained after selecting five features per fold from 219.The major feature types we evaluated are as follows: • Texture features: Co-occurrence Matrices, Laws Features. • Geometric features: Volume, Rectangular Fit, Compactness, Relative distance measure from pleural wall, • Intensity based features: mean brightness measure in terms of Hounsfield units (HU). All of these were used using classifiers And therefore classifiers were selected to test a range of techniques, and to determine those that provide the best predictive accuracy.They Are decision tree, upport vector machines , rule based classification, naive bayes. The data set used consisted of de-identified CT-scan images from the Moffitt Cancer Center, Tampa. The images are in the DICOM (Digital Imaging and Communications in Medicine) format. The data set consists of patients with tumor types of Adenocarcinoma and Squamous-cell Carcinoma. This paper focuses on the adenocarcinma patients. CT-scans of81 adenocarcinoma patients were used for survival time analysis. The slice thickness of the acquired CT-images ranged from 2.5mm to 6mm with an average thickness of 4.75mm

Tumor is an uncontrolled growth of cancer cells in any part of the body. Tumors are of different types and have different characteristics and different treatments [15]. At present, brain tumors are classified as primary brain tumors and metastatic brain tumors. Therefore, brain tumor are seriously endangering people's lives and early discovery and treatment have become a necessity. In the clinical aspect, treatment options for brain tumor include surgery, radiation therapy or chemotherapy. In current clinical routine, the images of different MRI sequences are employed for the diagnosis and delineation of tumor compartments. Due to the large amount of brain tumor images that are currently being generated in the clinics, it is not possible for clinicians to manually annotate and segment these images in a reasonable time. In this paper [9] These sequence images include T1-weighted MRI (T1w), T1-weighted MRI with contrast enhancement (T1wc), T2-weighted MRI (T2w), Proton Density-weighted MRI (PDw), Fluid Attenuated Inversion Recovery (FLAIR), These pre-processing operations include de-noising, skull-stripping, intensity normalization, etc, and have direct impact on the results of brain tumor segmentation. The nearer the data is to the cluster center the more possible its membership towards the particular cluster center is. The advantages of FCM algorithm include: (1) Giving the best result for overlapped data set and comparatively better than kmeans algorithm. (2) Unlike k-means where data point must exclusively belong to one cluster center. They concluded that the area under the ROC curve should be used for overall classification accuracy, MI is the metric of choice when interested in sensitivity to changes in tumor size, and the Dice coefficient is the best for the spatial alignment evaluation. Along with the advance of studies in the area, brain tumor automatic segmentation technology has the potential to provide better prognostic information and optimize treatment options.

Cancer is the leading cause of death worldwide. Cancer mortality can be reduced if are detected and treated early.In a first stage a cancer promotes an intense process of vascularization at the affected area increasing blood flow and modifying the local temperature of the body. Using a thermal camera, the infrared radiation emitted by the human body can be captured and then used in the measuring of body temperature, turning the results into an image. Moreover, thermography can detect suspicious regions in patients of any age, even in cases of dense breasts, where the detection of an abnormality cannot be accomplished by others exams. A fundamental step in the use of thermal images is the development of computer aided diagnosis (CAD) systems. In this work [10], an automatic detection of the regions of interest (ROI) is proposed and compared with segmentations performed manually. This work presents a methodology for the automatic segmentation of lateral breast thermal images. Finally, the obtained results by the proposed methodology for the 328 images used in this work are demonstrated. The results showed average values of accuracy.

The lack of publicly available ground-truth data has been identified as the major challenge for transferring recent developments in deep learning to the biomedical imaging domain. Though crowdsourcing (CROWDSOURCING according to this paper is a type of participative online activity in which an individual, an institution, a non-profit organization or a company proposes to a group of individuals of varying knowledge, heterogeneity, and number, via flexible open call, the voluntary undertaking of a task) has enabled annotation of large scale databases for real world images, its application for biomedical purposes requires a deeper understanding and hence, more precise definition of the actual annotation task. The fact that expert tasks are being outsourced to non-expert users may lead to noisy annotations introducing disagreement between users.In this paper [23] they present a new concept for learning from crowds that handle data aggregation directly as part of the learning process of the convolutional neural network (CNN) via additional crowdsourcing layer (AggNet). Their results give valuable insights into the functionality of deep CNN learning from crowd annotations and prove the necessity of data aggregation integration.

The most complicated structure of the human body is the brain and the segmentation of the brain needs to be precise and accurate But to do this it is very difficult because the shape is not in regular and investigation is difficult. Also segmentation is not easy which will consume lots of time and skilled manpower is required. Real time image processing requires processing on large data of image pixels in a stipulated time. Pathologists depend upon microscopic test of cell structure which uses old methods that consumes which will always gives error. If the uncontrolled growth of cells becomes more than 60 percent then the patient is unable to recover. So, it is must to have the fast and accurate detection of the brain tumor. Tumors are of mainly divided into two (1) beginning tumors or primary tumors Beginning tumors treatment for this type is not necessary are generally not need to be treated.(2)Malignant tumors.In this paper [28] They used certain techniques thresholding, Clustering, Watershed segmentation, Region growing, 6 Morphological Based Segmentation, Graph-based Detection. Efficiency of Robert, Prewitt, Sobel operator based edge detection systems is compared. FPGAs can be a promising solution for real time image processing work, to examine the real-time cancer images and provide better solution for analysis and diagnosis.

Breast density, a relative value for the amount of fibroglandular tissue (stromal and epithelial) in the breast, In this paper [29] The purpose of this study is to compare the measurements of breast density using three dimensional 3-D automated whole breast ultrasound ABUS and magnetic resonance imaging MRI.40 patients— bilaterally in 27 patients and unilaterally in 13 patients. To differentiate the fibroglandular and fatty tissues in ABUS and MRI images, the fuzzy C-mean classifier was used. Calculated values for percent density and breast volume from the two modalities were compared to and correlated with linear regression analysis. Mean percent density and breast volume derived from ABUS (17.63+-11.87 percent and 418.30+-132.97 cm3, respectively) and MRI images (23.79+-16.62 percent and 544.90+-207.41 cm3). As a conclusion ABUS and MRI showed high correlation for breast density and breast volume quantification.Both modalities could provide useful breast density information to physicians.

Breast density has been proven as an independent risk factor associated with the development of breast cancer [17]. One important step for quantitative analysis of breast density on MRI is the correction of field inhomogeneity to allow an accurate segmentation of the fibroglandular tissue (dense tissue). A new bias field correction method by combining the nonparametric nonuniformity normalization (N3) algorithm and fuzzy-C-means (FCM)-based inhomogeneity correction algorithm is developed in this work [16]. Also generated bias field is smoothed using Gaussian kernal and B-spline surface fitting. The performance of the new N3+FCM algorithm was comparable to that of coherent local intensity clustering (CLIC), showing equivalent quality in 57/60 breasts. This was applied on a total of 60 breasts from 30 healthy volunteers. As a conclusion The proposed algorithm combining N3+FCM and CLIC both yield satisfactory results.

In this paper [6] they investigate a new approach to the classification of mammographic images according to breast type. application aims to increase the sensitivity of detecting breast cancer. As the American College of Radiology (ACR) Breast Imaging Reporting and Data System (BIRADS), identifies four major groups for classifying breast density (Kopans [12]): (1) predominantly fat; (2) fat with some fibroglandular tissue; (3) heterogeneously dense.; (4) extremely dense. In this study they examine two different classification tasks; a four-class classification problem differentiating between breast densities following the BIRADS classification and a two-class problem, differentiating between dense and fatty breast types. They evaluated 377 mammograms from the Digital Database of Screening Mammograms (DDSM) [20].In this study they employ four approaches for determining texture; 1) By constructing Spatial Grey Level Dependency (SGLD) matrices [19] using the directions 0, 45, 90, 135 degrees and pixel distances 2, 4, 6, we extract 15 features. These features include angular second moment, contrast, correlation, inverse different moment, sum average, sum variance, sum entropy, entropy, difference average, difference variance, difference entropy, information measure of correlation I, information measure of correlation II, inertia, variance ; 2) Following the application of the Fourier transform, we extract the total spectral energy from 10 equidistant analysing rings from the power spectrum [26]; 3) By convolving each mammographic image with each combination of Laws' texture masks [13], we extract the total texture energy for this mask combination for use as a feature. 4) Following application of the Discrete Wavelet Transform (DWT), four features (standard deviation, mean, skewness and kurtosis). They also used Artificial Neural Network (ANN), Principal Component Analysis (PCA). And an average recognition rate on test of 71.4 percent for the four-class problem and 96.7 percent for the two-class problem.

In [11], They propose a brain tumor segmentation and classification method for multi-modality magnetic resonance imaging scans. The data from multimodal brain tumor segmentation challenge (MICCAI BraTS 2013) are utilized which are co-registered and skullstripped, and the histogram matching is performed with a reference volume of high contrast. From the preprocessed images, the following features are then extracted: intensity, intensity differences, local neighborhood and wavelet texture. The integrated features are subsequently provided to classifiers (kNN, RF, AdaBoostM2 and RusBoost) predict five classes: background, necrosis, edema, enhancing tumor and non-enhancing tumor, and then these class labels are used to hierarchically compute three different regions (complete tumor, active tumor and enhancing tumor). They performed a leave-one-out cross-validation and achieved 88 Dice overlap for the complete tumor region, 75 for the core tumor region and 95 for enhancing tumor region, which is higher than the Dice overlap reported from MICCAI BraTS challenge

Mammography is the gold standard for breast imaging and cancer detection. However, due to some limitations of this modality such as low sensitivity especially in dense breasts, other modalities like ultrasound and magnetic resonance imaging are often suggested to achieve additional information. Recently, computer-aided detection or diagnosis (CAD) systems have been developed to help radiologists in order to increase diagnosis accuracy.Generally, CAD systems are classified into two categories: computer-aided detection (CADe) and computer-aided diagnosis (CADx) systems. The CADe systems are developed to help the radiologist in detecting and locating the abnormal area in images, while the CADx systems are designed to diagnose and classify benign or malignant tissues. This paper[3] represent that the CAD sensitivity reported for cancer detection is over 90 Percent with higher sensitivity for detecting classification than architectural distortions or masses. Reportedly, the CAD system assists radiologists and increases detection sensitivity of breast cancer up to 20 percent.

3.1 Comparison with proposed Project

• In similar system for brain tumor they applied algorithms as BCN and FCN and Expectation maximization. They used BRATS dataset for 2013/2015. In Breast similar system they also used Expectation Maximization and the dataset used were 50 mammography cases. In lung similar system they used RASM algorithm. Our proposed system will apply CNN classifier and K-means segmentation algorithm using MIAS dataset for Breast and BRATS dataset for brain and Luna for Lung.

Points Of comparison	Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images	Breast Segmentation and Density Estimation in Breast MRI: A Fully Automatic Framework	Automated 3-D Segmentation of Lungs With Lung Cancer in CT Data Using a Novel Robust Active Shape Model Approach	Our Proposed System
Algorithms	BCN, FCN, Expectation Maximization	Expectation - maximization (EM)	(RASM)	CNN, K mean and FCM
Dataset	BRATS Dataset 2013/2015	50 cases	30 data sets with 40 abnormal (lung cancer) and 20 normal left/right lungs	MIAS BRATS
Accuracy The DSC [51] measures the overlap between the manual and the automatic segmentation	DSC score of 0.78, 0.65, and 0.75	The average DSC value was 0.94 ± 0.03 (mean ± sd	Dice coefficient of 0.975 ± 0.006	_
Type Of cancer	Brian	Breast	Lung	Brain, Lung, Breast

Figure 7: Comparison

4 Project Management and Deliverable

4.1 Tasks and time plan

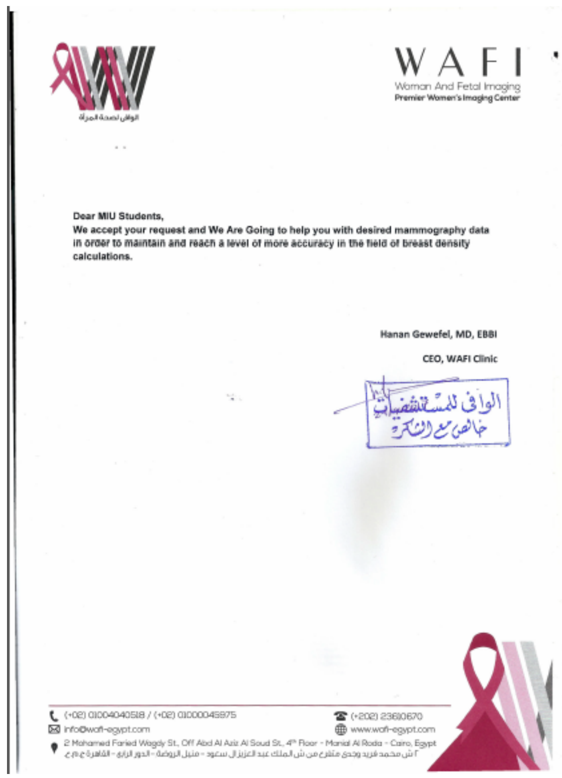
Phase	Start Date	End Date
Proposal Evaluation	26 sep 2017	27 sep 2017
SRS Evaluation	10 Nov 2017	
Prof. Jiro Tanaka	3 Dec 2017	11 Dec 2017
SDD Evaluation	17 Jan 2018	
Evaluation Implementation	30 March 2018	
Delivering 6 pages paper	12 April 2018	
Technical Evaluation	1st week of may 2018	
Final Thesis	26 June 2018	

Figure 8: Time Plan

4.2 Budget and Resource Costs

ZERO

4.3 Supportive Documents



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