ZANCO Journal of Pure and Applied Sciences

TYPE Original article
DOI http://dx.doi.org/10.21271/ZJPAS.37.5.8

OPEN ACCESS

*Corresponding author
Mahdi S. Raza
mahdi.raza@su.edu.krd

RECEIVED :10 /09 /2024
ACCEPTED :14/05/ 2025
PUBLISHED :31/ 10/ 2025

KEYWORDS:
Survival analysis, Cox. Regression model, Mask R-CNN, MRI, Breast Cancer, Tumor size, and Boosting Mask RCNN.

Using Deep Learning Boosting with Survival Analysis for Breast Cancer Diagnosis

Mahdi S. Raza[1] , Abbas M. Ali[1] & Chiman Haydar Salh[2]

1 Department of Software Engineering and Informatics, College of Engineering, Salahaddin University-Erbil, Erbil 44001, Iraq
2 Department of Information System Engineering, Erbil Technical Engineering College, Erbil Polytechnic University, Erbil 44001, Iraq

ABSTRACT

Around the world, women are diagnosed with breast cancer, which is a deadly disease. Early detection is very important in helping improve the survival rate and advance the excellence of care for patients. With the help of deep learning models, medical image analysis can be performed with high accuracy and can even be used to automatically identify breast cancer. Several research has been undertaken on the application of survival analysis and deep learning models for the detection of breast cancer. This work introduces a methodology that can effectively and precisely diagnose breast cancer with reliability. This approach utilizes survival analysis and Deep learning, enhanced with statistical techniques such as the Cox regression model and Kaplan Meier Method. Additionally, a dataset of breast cancer magnetic resonance imaging (MRI) has been created and refined. The study findings demonstrated that the utilized model for the survival analysis of breast cancer exhibited excellent performance, achieving a remarkable accuracy rate of 98%. The improved Mask R-CNN with the scanner known as enabled the comparison of tumor size and breast size.

1.Introduction

In 2021, about 30% of all new female cancer cases in the US will be attributed to breast cancer (Militello et al., 2022). The survival rate has significantly improved due to effective screening and early detection. Early detection is very important to treat this disease effectively (Michael et al., 2021) .

Early detection and screening are very important in order to reduce the mortality rate and improve the survival rate. Artificial intelligence is a powerful tool that can help in the development and implementation of effective interventions and care plans. It can also analyze and resolve problems related to the diagnosis and treatment of cancer (Kim et al., 2020). Medical images are used to diagnose cancer.

Medical imaging can help identify various disorders and evaluate the results of studies (Yassin et al., 2018). Moreover, it plays a vital role in cancer treatment (Nayak et al., 2022). Studies have shown that MRI can be used to diagnose breast cancer. This type of imaging allows researchers to visualize the different anatomical structures and physiological characteristics of the tissue (Nayak et al., 2022).

Recent studies have shown that algorithms for extracting features from MRI scans can help identify breast cancer tumors and predict the outcome of patients (Ivanovska et al., 2019). The use of machine learning techniques in MRI scans for detecting breast cancer volume is an important advancement in this field.

When it comes to planning a breast cancer surgery, the volume of the affected tissue is a vital factor that is used to determine the optimal course of action (Di Micco et al., 2017) . In most cases, this process can be performed in combination with other factors such as the size of the tumor and the expected recovery time (Wang et al., 2022). However, it is not easy to know the exact volume of the affected tissue due to the complexity of the procedure.

Currently, there is a lack of a single, reproducible, and easy-to-use method for estimating the volume of breast tissue during a medical procedure. A surgeon's assessment of the patient's anatomy is carried out by subjective observation.

There are various methods that are commonly used to calculate the volume of breast tissue. One of these is the Archimedean method, which is based on the use of water displacement techniques (Cai et al., 2019). Although the Archimedean method is more accurate than the other methods, it is not the same as the other methods used to determine breast size.

One of the most common methods used to determine the volume of breast tissue is mammography, which is a standard procedure that involves multiple formulas and techniques. Although CT and MRI are also available, they are not routinely used for the diagnosis of breast cancer (Ren et al., 2022).

In addition to mammography, MRI is also commonly used for projection and volume estimation during cosmetic surgery. Although its clinical utility has not yet been fully explored, breast volume detection using MRI is a more recent option. This study aimed to evaluate the accuracy of this method in estimating the volume of breast tissue in patients who were undergoing WLE or mastectomy (Gouveia et al., 2022).

Several studies in this area are currently being conducted. One of these involves developing computer-aided segmentation techniques for detecting breast cancer tumors using MRI images. This paper presents a new method for diagnosing breast cancer by combining deep learning with boosting techniques within the framework of survival analysis. The contributions of this research are multifaceted and can be summarized as follows.

The researchers employed deep learning models, including Mask R-CNN, and Resenet152v2. They were able to detect and categorize breast cancer in MRI images.Utilizing the Cox regression model and Kaplan-Meier technique has boosted the accuracy and dependability of breast cancer detection by integrating survival analysis with deep learning. Developing and improving a breast cancer MRI dataset to facilitate analysis. Improving the ability to diagnose breast cancer at an early stage is vital for increasing the chances of survival and providing better quality treatment for patients.

The paper's structure suggests that the system should be divided into two phases. The first stage involves analyzing the abnormal dataset using Mask R-CNN. The second stage involves using the Cox regression model and the Kaplan-Meier technique has been boosting the accuracy and dependability of breast cancer detection by incorporating survival analysis with deep learning. The paper's structure continues to explain the various steps involved in the development of the system. The results of the simulation and the experimental setup are then presented at the end of the study.

2. Related work

Breast cancer is widely recognized as one of the most prevalent diseases affecting women. To accurately diagnose this condition, medical professionals typically rely on mammography screening and MRI breast cancer imaging. Thanks to the advancements in deep learning, researchers have been able to develop models that can predict the likelihood of an individual developing breast cancer even before an official diagnosis is made. These models are capable of analyzing various data sources to identify patterns and provide valuable risk assessments. Table 1 presents a compilation of literature reviews pertaining to this technique (Alikhassi et al., 2018).

However, a limitation of these studies is that not all forms of tumors have been identified to a degree that allows for their use in future therapies, such as determining the type of breast and tumor size. In this particular study, four different types of breasts were identified using various models applied to mammogram images.

The study employed multiple models, including CNN, Mask R-CNN, and Resnet152V2, to accurately detect tumors based on mammograms. The utilization of deep learning models has become a common approach in current research studies focused on breast cancer diagnosis and detection (Cai et al., 2020, Salh and Ali, 2023).

Since deep-learning evolved in so many areas, the use of these techniques in papers for segmentation or classification is more and more common. As a result, statistics with deep learning are applied in this paper for clustering of malignant and benign cells in mammography images. This way it is thought that doctors will be able to diagnose patients more quickly and offer them the best treatment (Ackermann et al., 2022).

An MRI scan is used to analyze breast cancer. It can detect the growth of the tumor and its health. However, its volume and estimation are mainly affected by the time-consuming process of searching for and setting criteria.

In order to improve the efficiency of this process, a team of researchers developed a new method that uses deep learning to analyze the volume of breast cancer tumors. This method was able to detect the disease in its early stages.

Through deep learning, researchers were able to create models that can predict a person's likelihood of being diagnosed with breast cancer. This technology has revolutionized the field of cancer treatment and has allowed scientists to create more effective and precise methods that can save lives(Chen et al., 2021). Unfortunately, most studies on the use of this technology have not been able to provide adequate findings for a long time.

Table 1 depicts the categorization of tumor size (T) and lymph node involvement (N) in breast cancer. Below is a comprehensive analysis of each category along with its corresponding description.

Table 1. Information for stage tumour size and lymph nodes for Breast cancer

	T1	**T2**	**T3**	**T4**
Stage tumour Size T	Diameter of the stage tumour size less than 2 cm. 	Diameter of the stage tumour size greater than 2 cm and smaller than 5 cm. 	Diameter of the stage tumour greater than 5 cm. 	Stage tumour size breaches the skin or the rib cage. 
	N 0	**N 1**	**N 2**	**N 3**
Lymph Nodes N	Empty cancerous cells in the lymph nodes.	The similar side of the unhealthy breast, the cancer spreads to non-adjacent Stage lymph nodes under the axilla.	Cancer metastasizes to internal lymph nodes in the breast or spreads to nearby stage lymph nodes below the axilla from the similar side of the infected breast.	Cancer spreads to internal stage lymph nodes in the breast, under the axilla, and under or above the clavicle.

Based on 3 cm measures, there are typically three stages for tumor grade: There is also small which is about 3cm; medium, which is more than 3 cm but has not affected the chest; and giant which is the cancer cells have advanced to the next level. These ratings are based on the amount of Tumor sizes added up cumulatively.

Under a microscope, pathologists examine breast cancer samples to evaluate the tumor's grade, which is based on how closely it resembles healthy breast tissue. Usually, looks like cancers that nearly mimic healthy breast tissue and spread very gradually and receive a lower grade. It generally denotes a less probable cancer to spread, while a higher grade denotes a more likely cancer to spread. Tumor grade on the other hand depends on the relative position of the cells thus the arrangement of the cells in the form of tubules, the size of tumor less than 1cm in diameter, nuclear grades and finally the mitotic count. Owing to the fact that the malignant feature very closely mimics normal breast cells, a small tumor-grade malignancy might be termed ‘well-differentiated’. Likewise, since the cells of a large tumor grade are no longer normal breast cells, they might also be called “poorly differentiated”. Table 2 shows that the small tumour grade is classified by (1), the medium tumour grade by (2), and the large tumour grade by (3).

Table 2 displays the descriptive statistics for three factors pertaining to breast cancer patients:

Age, Tumor Grade (measured in centimetres), and Survival Time (measured in days). Below is a comprehensive breakdown of each row in the table.

Table 2. Survival time for the variables age and tumour size

Statistical Methods	Age	Tumour Grade (cm)	Survival Time(day)
N	1163	1163	1163
Missing	0	0	0
Mean	49.37	1.77	762.92
Std. Er. of Mean	.340	.019	21.634
Median	48.00	2.00	704.00
Stdard Deviation	11.59	.632	737.78
Variance	134.4	.400	544328
Range	72	2	6770
Minimum	20	1	3
Maximum	92	3	6773

Table 3. Information for stage tumor grade.

Tumor Grade		Frequency	Percent
Stage tumour grade	Stage (I)	397	34.1
	Stage (II)	637	54.8
	Stage (III)	129	11.1
	Total	1163	100.0

The stage tumour grade table, which shows how quickly a cancer is expected to grow and spread in the breast, is shown in Table 3. It reveals that the tumour grade in 54.8% of patients is moderate. Cancer cells develop more quickly than normal cells and do not resemble normal cells. The cancer cells can be eliminated, therefore even if 11.1% of them have a late diagnosis, their treatment is simpler than that of the medium grade. Because tiny tumours typically grow more slowly, early diagnosis is preferable for controlling this kind of cancer, which accounts for 34.15% of patients at Erbil and Sulimani Hospital.

3. DEEP LEARNING MODELS

There are diversified types of deep learning and these are at times used in analyzing images in clinical practice. That is, most researchers, as marked by references, have chiefly conducted studies with the detection of disease and diagnosis using images acquired at a single point in time of patient care (Altini et al., 2022).

Lately, some other hopeful models of deep-learning and computer vision including Convolutional Neural Networks (CNN), deep learning-based object detection models and transfer learning, have shown a vast improvement in the performance of Computer-Aided Diagnosis (CAD) systems. Algorithms proposed for CAD systems are related to deep learning models as follows: Deep learning has proposed a CAD technique that marks, segmental and categorize mammographic images linked to masses with little assistance from the user (Whitney et al., 2019, Zhang et al., 2023) .

3.1 ResNet152V2

ResNet152V2 is a recently introduced deep CNN architecture that has gained significant success in medical imaging applications (Lin et al., 2022). The architecture has demonstrated its effectiveness by utilizing residual blocks with skip connections between layers, allowing for simultaneously bypassing multiple convolution levels. This approach is effective in terms of simple representation of input images and boosting the achievement of classification tasks due to the increased rate of convergence of many layers. ResNet architecture provides multiple standard architectures including ResNet-50, ResNet-101, and ResNet-152 to define the depth of layers involved. Alternatively, a superior version of ResNet, known as ResNetV2, eliminates the final ReLU to enable a direct identity connection for shortcut paths (Saber et al., 2021, Kumaraswamy et al., 2023). The ResNet-152 achieves the highest accuracy on the training and testing datasets. This algorithm distinguished between normal and abnormal breasts with a 98.00% accuracy rate. Using ResNet-152 yields the highest sensitivity results. As in Fig.1

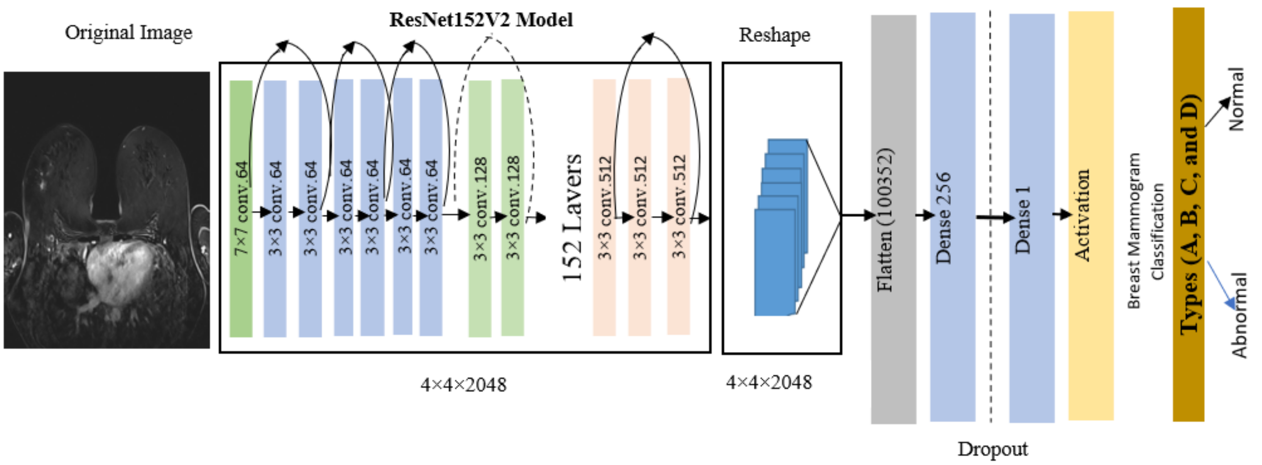

Figure 1. ResNet152V2 structure

3.2 Mask R-CNN Model

Given that the Mask RCNN model is an extension and enhancement of the Faster RCNN, it stands as the most advanced neural network primarily employed for instance segmentation. While Mask RCNN is commonly utilized for object detection, its versatility across diverse data sets, as described in their initial studies, make it a great tool for most medical image analysis-based research (Raza, 2016). Previously, Faster R-CNN has been utilized for drawing bounding boxes and classifying input images. However, with the advent of Mask R-CNN, which is series version of Faster R-CNN, the complete architecture of Faster R-CNN is retained, while an additional branch is incorporated simultaneously with the existing branch utilized for prediction of object mask (Surendhar and Vasuki, 2021, Avcı and Karakaya, 2023) . Mask R-CNN can be effectively applied to a wide range of other datasets and is relatively straightforward to train.

For object recognition and segmentation, one of the impressive methods is the Mask R-CNN. It not only accurately localizes and drawn a rectangular box around the particular object of interest but also simultaneously labels and categorizes the pixels in that box. This makes it possible to point to the object, to define the limits to the object or to detect critical areas (Chiao et al., 2019). In this study, Mask R-CNN is used to detect an object to identify different components in an image and encase a malignant object with a bounding box while leaving a benign one alone as shown in Fig 2. In this study, for ease of analysis and description of the target malignant tumor location in the mammography, the area is referred to as the region of interest (ROI). If the size of the tumor is small then the program of Radiant must be used to know the sizes mentioned.

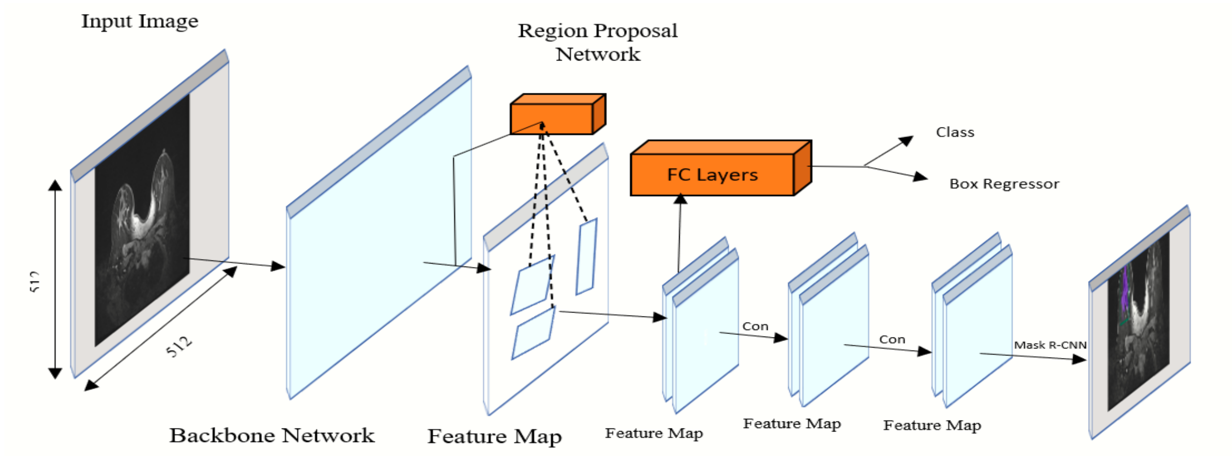

Figure 2. The architecture of Mask R-CNN.

3.3 Detectron2

Detectron2 is a type of deep learning toolbox commonly used for visual applications. It is constructed to be simple to switch between many tasks like instance segmentation, and object detection(Ahmad and Mouiad, 2021). It is commonly used in some datasets like COCO, LIVS, and Pascal VOC (Nasser and Yusof, 2023). This model's backbone is combining Faster with Mask R-CNN and Resnet152V2. Also, it delivers ready-to-use baselines with pre-trained weights (Pham et al., 2020). The most modern object identification using Python language is a module from the AI research team of Facebook known as Detectron2.

This paper utilizes the training of Mask R-CNN on a conventional dataset using Detectron2, for MRI images in breast cancer images is shown in Fig. 3.

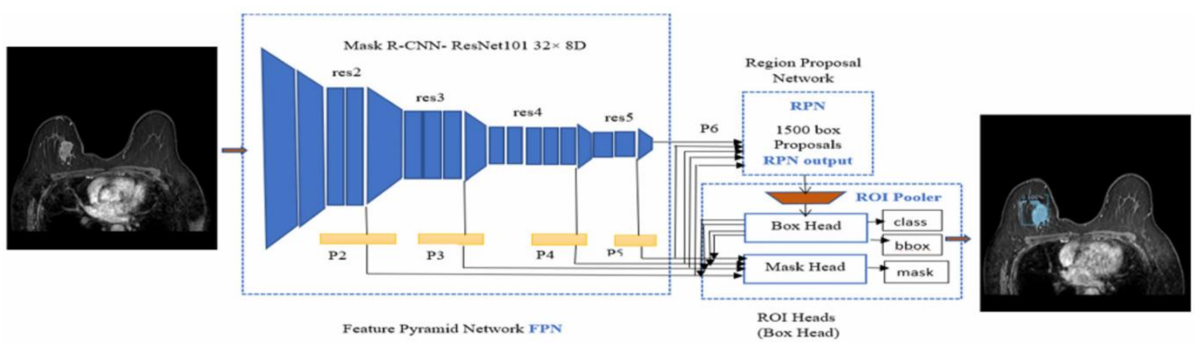

Figure 3. The architecture of Decatron2(Ahmad and Mouiad, 2021)

4. PROPOSED METHODOLOGY

The breast cancer survival analysis model was created by integrating the deep learning model with the statistical method to increase the accuracy, as seen in Figure 1. Initially, the original data from the BC registry in a hospital in Erbil and Suleimani throughout 2020-2022 was studied. Subsequently, the patients with BC were screened for Tumour Grade, age, and Survival Time. It is then split into two distinct stages. The initial phase entails examining the anomalous dataset using Mask R-CNN. In the second step, the breast tissue volume is compared with the tumor volume using Detectron2. This is done to establish the relationship between these variables and the individual's survival status. In addition, the researchers utilized the Kaplan-Meier univariate survival analysis to examine the duration of survival in patients with BC as shown Fig.4. They applied the logarithmic test to assess the significance of the findings. The Cox proportional hazards model was utilized to assess the predicted parameters that influence the survival time, including patient characteristics, treatment approach, and operation (Raza, 2016).

The purpose of this paper is to develop a deep learning framework for doctors to make analytic judgments. The patient's danger factor MRI data which are related to breast cancer is then fed to the breast cancer identification model after which the current status of the patient is classified as either normal or abnormal using ResNet152V2. When the outcome is anticipated, the patient is then usually followed up. The outline of the proposed design is therefore characterized by three big sections. At the start, the given dataset was introduced, subsequently, the given dataset was divided into three parts (Raza and Broom, 2023).

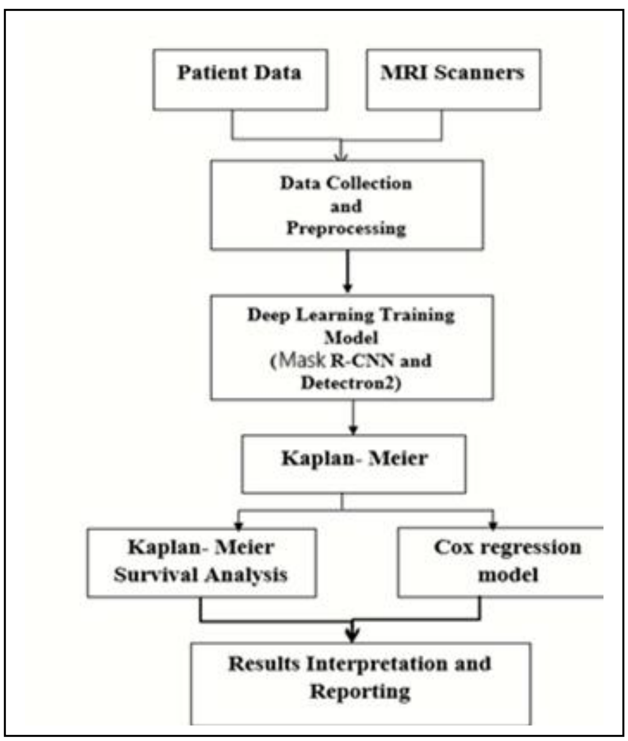

Figure 4. The proposed method data flow diagram.

4.1 Dataset

The MRI dataset used in this study was collected from Sulaymaniyah and Erbil hospitals. To better understand the data, we carried out a deeper analysis of how malignant and benign cases were spread across the patients. Among 145 patients and 2,175 images, we found that 65% were diagnosed with cancer, 35% had benign tumors, and 20% of the patients had undergone mastectomy. For building the model, we randomly selected 1,700 images.

Two experienced radiologists reviewed the MRI scans and sorted them into four categories based on the level of fibroglandular tissue. Category A includes women with mostly fatty breast tissue, making up about 10% of cases. Category B shows scattered areas of dense tissue, seen in around 40% of women. Category C features heterogeneously dense tissue, also covering about 40%. Finally, Category D includes women with extremely dense tissue, found in about 10% of cases.

It's important to note that detecting tumors becomes much more challenging in Categories C and D because the higher tissue density can hide abnormalities in the images

4.2 Preprocessing Datasets

Pre-processing gets data ready for analysis or machine learning by turning unstructured information into a usable format. This study aims to build a model that can identify normal, malignant, and benign tumors, as well as classify different breast density types from mammograms. The process is divided into three phases, starting with collecting the dataset and moving through three stages of preparation.

4.2.1 Data Augmentation Algorithm (DAA)

The Data Augmentation Algorithm (DAA) is a method that leverages machine learning and computer vision to expand datasets. This approach is especially important when working with limited data, as it helps boost the performance and adaptability of machine learning models. In this project, a range of transformations is applied to the training data. One common technique we use is flipping, a popular method of data augmentation.

There are two main types of flips: vertical (along the y-axis) and horizontal (along the x-axis). For this model, we focused on the horizontal flip, where each image in the dataset is mirrored vertically. In simple terms, the left side of the image becomes the right side, and vice versa. The detailed process of the data augmentation is illustrated in Figure 4. As a result, every input image produces two versions.

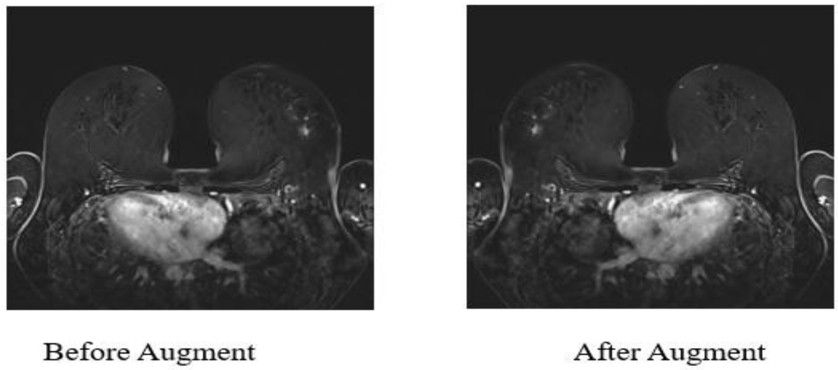

Figure 5. Rotating images around the x-axis

4.2.2 Data Resizing

The routine level of the input data should be optimized at this stage since adding extra layers means increasing the degree of calculation without enhancing the result in most cases. This task is made possible by using $Python/keras.preprorocessing$ library. From the series of the experiments made in regard with various image dimensions, we have reached the conclusion that, in order to minimize the image dimensions by 48 x 48, the image dimension has to be 512 by 512. This approach makes it possible to ensure that diagrams are easy to interpret while at the same time making the computations involved in their interpretation complicated.

4.2.3 Data Reshaping Process

This stage is used to modify the input layer of ResNet-152V2 in such a way to be able to take the input shape for our pre-processed data set (Imagewidth = 48, Imageheight = 48, Noofchannels = 1). This is done with the help of the PyTorch/Keras pre-processing library.

The three fundamental stages of the model proceed after the acquisition of the dataset. The first step focus on the utilization of ResNet152 V2 to classify between normal and abnormal MRI scans. The second stage uses an improved Mask R-CNN to segment the breast MRI images of the benign and malignant types. The final stage involves using Mask R_CNN for the differentiation between malignant and benign and the determination of the size of the tumour area. In the next step, it is important to find out that 1 cm is equal to every 790 pixels of an image and that was found out by the radiology doctors with the help of the Radiant DICOM Viewer program. Some of this information is used to calculate the size of the tumor in its area. The size of the tumor area is then computed using Mask R-CNN regarding the region of interest (ROI) of each image as shown in Equation 1.

Area tumor = (area Mask)/(790 pixel) .... (1)

5. EXPERIMENTAL WORK AND RESULT

5.1 EVALUATING METHODS

In the present study, the feature selection has been conducted on the dataset obtained from a real hospital. Moreover, three feature-selection techniques including ResNet152V2, and Mask R-CNN were performed. The system entails three models only which are designed for the MRI images of breasts. The ROC results averaged for all ResNet152V2 comparisons with the normal and abnormal breast include ROC curves of 0.979 for the left class, ROC curves of 0.979 for the right class, and an AUC of 0.979. This model took a total of 2.26 seconds to undergo training.

This form of evidence justifies the credibility of our study as follows. Our evaluation of the models, as depicted in equations (2) to (6), incorporates four ways: the F-Score (FS), accuracy (AC), precision (PR), sensitivity (SE), and specificity (SP). The abbreviation TP stands for the number of True Positive while Tn is the number of True Negative, FP for the number of False Positive, and FN is the number of False Negative (Qi et al., 2019).

SE= TP/(TP+FN)……………………..........(2)
PR = TP/(TP+FP) ....(3)
SP = TN/(TN+FP) .... (4)
F-Score= (2×Percision ×Sensitivity) / (Precision + Sensitivity) ....(5)
AC = (TP+TN)/(TP+TN+FP+ FN)..............(6)

5.2 EXPERIMENTAL SETUP

The experimental work in this paper was performed on Python 3 and GPU. The enhanced Mask R-CNN was performed using the Keras package. The dataset was subdivided into 3 sections: These include 80% for training the model to get the best option 10% for testing the results of the model on unseen data known as the testing dataset, and a further 10% as the validation dataset for further training of the model. Firstly, the feature of MRI pictures and the fine positioning pictures given by the doctor were utilized to interpret the clusters of the calcification points into normal and abnormal in the ResNet152V2 model set for optimizing the model, a 10% testing dataset for assessing the model's performance on unseen data and testing results, and a 10% validation dataset for further model optimization. Initially, the MRI images and fine positioning images provided by the doctor were used to realize the clusters of calcification points, separating them into normal and abnormal in the ResNet152V2 model. Lastly, by applying the optimized Mask R-CNN model, the clusters were identified and categorized either as benign or malignant, and the size of the tumours was determined. To achieve this, a certain number of experiments were performed for each chosen batch size (1) and number of epochs (50).

6. Results and Discussions

6.1 Implementation of the Detectron2 and Mask R-CNN

After successfully installing Detectron2, we used its pre-trained models to train our dataset, focusing mainly on working with Mask R-CNN and Detectron2 frameworks. To evaluate the performance of each model, we relied on the Average Precision (AP) metric, a widely recognized measure for ranking object detection models. Detectron2 also uses Average Recall (AR) alongside AP to provide a clearer picture of how accurately objects are detected. As mentioned earlier, the dataset was divided into separate training and validation sets to ensure fair testing. In the visual results, the original reference image appears on the left, while the detection results—after applying the algorithm, are displayed on the right as shown in Fig.6. These results illustrate how the Mask R-CNN model, supported by Detectron2, can automatically detect, classify, and localize abnormalities in breast MRI scans, offering valuable assistance to radiologists in identifying critical areas more quickly and accurately.

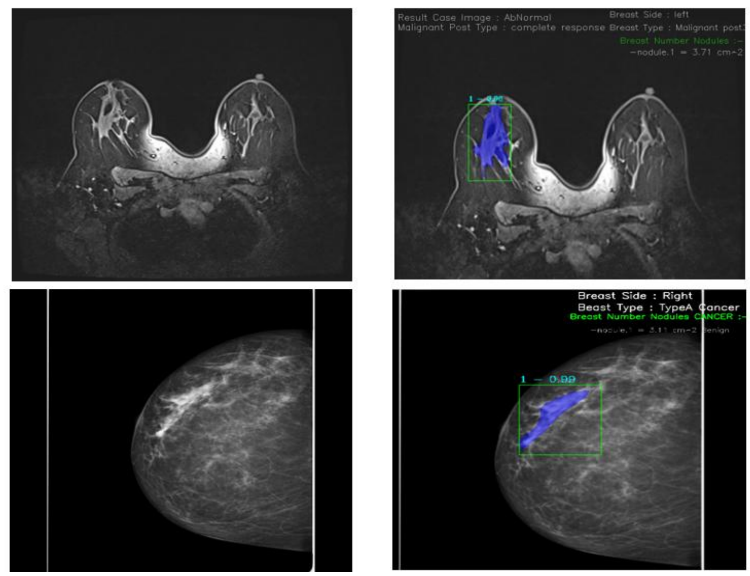

Figure 6. Example breast cancer detection using Mask RCNN and Detectron2

The log-rank test findings for the tumor grade, the study's final significant variable, are shown in Table 4. It demonstrates that the gap between tiny and medium-sized people is greater than that between large and small people. Using the Chi-Square test and Log-Rank (Mantel-Cox) test, the table presents a statistical analysis that compares different tumor grades (Stage (I), Stage (II), and Stage (III)). These tests are used to assess the significance of variations in survival distributions. This table facilitates comprehension of the comparative survival results across various tumor grades, revealing substantial distinctions solely between Small (I) and Medium (II) grades (Raza, 2016).

Table 4. The stage tumour grade by using test of Log-rank for the variable in Erbil and Suleimani data.

Stage tumor grade		**Stage (I)**		**Stage (II)**		**Stage (III)**	
		Chi-Square	*p*. value	Chi-Square	*p*. value	Chi-Square	*p*. value
Log-Rank (Mantel-Cox)	Stage (I)			9.404	.002	3.467	.063
	Stage (II)	9.404	.002			.069	.793
	Stage (III)	3.467	.063	.069	.793		

The Kaplan-Meier survival curve graphically illustrates the odds of survival over time for patients with varying tumor grades: Stage (I), Stage (II), and Stage (III). In Fig 8 is a breakdown of the main elements depicted in the graph.

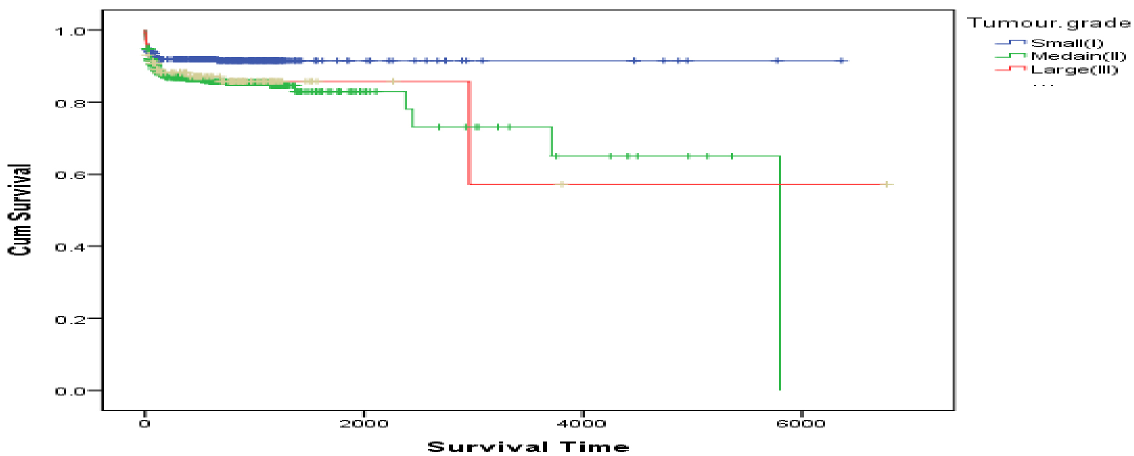

Figure 8. Stage tumour grade for curve of Survival function by using Kaplan-Meier method in Erbil and Suleimani data

Fig 8 illustrates that patients with a low tumor grade have a greater survival rate compared to those with medium and big tumors. Additionally, the function of cumulative survival for medium-grade tumors is larger than that for large-grade tumors.

The diagram is a Kaplan-Meier curve in Fig.9, commonly referred to as a survival curve, illustrating the likelihood of people in a certain group surviving for a given duration of time. The vertical axis of the graph displays the cumulative survival rate, which is the percentage of the group that remains alive for a specific duration of time or longer. The x-axis represents the duration of survival (Raza, 2016).

The graphic depicts the survival rate of two distinct age groups. The caption indicates the presence of two groups: one with an age of 48 or younger (labelled as "Age <=48 (1)") and the other with an age greater than 48 (labelled as ">48 (2)"). Regrettably, the data about the group aged 48 and above has been redacted. Consequently, the data about their survival rate beyond a specific threshold is not accessible.

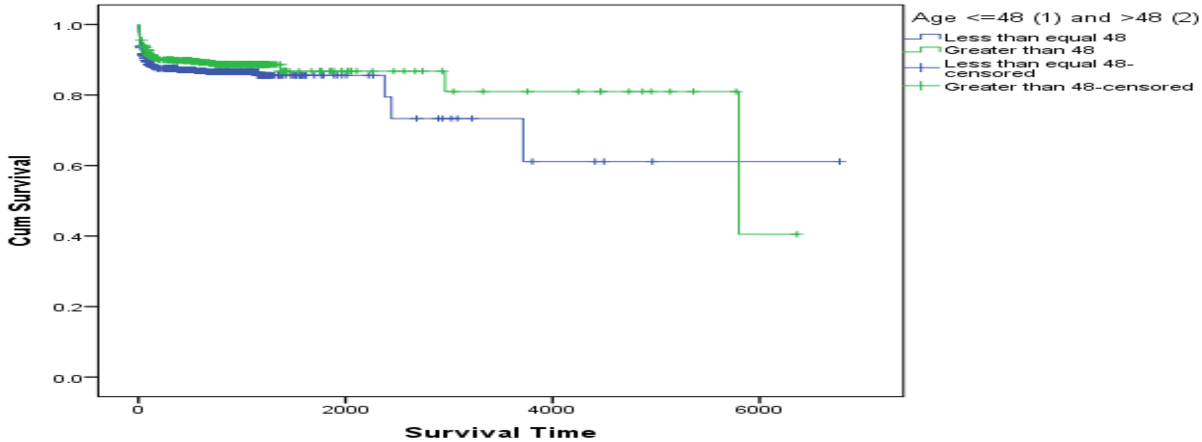

Figure 9. Age <= and > 48 years for the Erbil and Suleimani data by using the Cumulative survival function.

6. Discussion and results

Breast cancer is a prominent global health issue that impacts women on a global scale. Despite significant advancements in the field of medical research, a conclusive remedy for breast cancer continues to be evasive. Nevertheless, recent improvements in artificial intelligence (AI) have created new opportunities for the early identification of diseases and enhanced patient survival rates. Deep learning technologies have become prominent because they can automatically extract useful characteristics from complicated data. The recognition of breast cancer using methods of deep learning. Researchers conducted a thorough literature study to explore several deep-learning techniques for identifying breast cancer. Their attention was directed towards genomes and histopathology imaging data (Nasser and Yusof, 2023) . Convolutional Neural Networks (CNNs) have become the most precise and often utilized model for detecting breast cancer. These neural networks provide exceptional performance in tasks related to pictures and have exhibited encouraging outcomes in detecting malignant areas from mammograms and histological images. In contrast to standard machine learning approaches, deep learning needs minimum human involvement in the feature extraction process. This automation simplifies and optimizes the diagnostic procedure. Model performance is frequently assessed by researchers using accuracy measures. These metrics encompass sensitivity, accuracy, and the area under the curve (AUC). Analysis of survival Utilizing the principles of Machine Learning Survival analysis seeks to forecast the duration until a certain event, such as death or recurrence, takes place. Researchers have checked the use of machine learning algorithms to predict the prognosis of breast cancer (Lopez-Almazan et al., 2022).

A comparison is conducted on the outcomes of breast cancer MRI detection algorithms, using a dataset collected from Erbil Hospital. The research incorporates doctor data with the assistance of radiologists, resulting in high accuracy. The selected subjects' medical image data is utilized, revealing the presence of breast cancer in every MRI, albeit with varying locations, kinds, and forms of lesions. To ensure fairness, the samples are randomly divided into process of training sets, test sets, and validation sets. The models are compared based on the employed algorithms and the utilization of Mask R-CNN as in(Tahir, Ali and Hadi, 2024).

The dataset was gathered from a hospital. After selecting the features, three algorithms were then used: CNN, Mask R-CNN, and ResNet152V2. The three models are used for analyzing breast mammogram images.

In Table 5, the network accuracy performance of CNN has been shown to have accuracy more than 0.98% for the right and left regions. The performance of the breast density classification method defined in Table 6 uses ResNet152V2, while Table 7 indicates the detection rate using Mask R-CNN.

The following suggested approaches had a sensitivity of 97%, specificity of 0.98% and accuracy of 0.99%.

The performance of the suggested approaches was analysed based on some measures including precision (AC) sensitivity (SE) F-Score (FS), and specificity (SP). The outcomes reveal that the shapes derived from the models can identify false negatives and true positives.

Table 5. classification performance of Breast cancer of CNN model for left and right

Evaluation	Sensitivity	Specificity	Precision	F-Score	Accuracy
Left	0.959	0.983	0.980	0.969	0.976
Right	0.968	0.973	0.940	0.956	0.986

For left and right breast cancer categorization, the CNN model shows quite good performance; right breast achieves better accuracy (98.6%). Slightly lower precision for the right breast (94.0%) suggests minor false positives, but overall performance is robust.

Table 6. Classification ResNet152V2 of Breast density type.

Method		Sensitivity	Specificity	Precision	F-Score	Accuracy
Type A	Abnormal	0.964	0.927	1.000	1.000	0.986
	Normal	1.000	1.000	1.000	1.000	1.000
Type B	Abnormal	0.940	0.889	0 .85	1.000	0.939
	Normal	0.943	1.000	0.96	0.893	0.943
Type C	Abnormal	0.917	1.000	0.96	0.840	0.913
	Normal	0.980	1.000	0.97	0.960	0.980
Type D	Abnormal	0.914	0.842	1.000	1.000	1.000
	Normal	1.000	1.000	0.970	1.000	0.980

Type A (Normal) achieves perfect scores (100%) across all metrics.

Type B (Abnormal) shows lower precision (85%) and F-score (89.3%), likely due to class imbalance or challenging samples.

Type D (Abnormal) has high sensitivity (91.4%) but lower specificity (84.2%), indicating potential false positives.

Overall, ResNet152V2 struggles with Type C and D Abnormal cases, suggesting limited generalizability for dense breast tissue.

Table 7. Performance of Breast cancer categorization using Mask R-CNN.

Method	Sensitivity	Specificity	Precision	F-Score	Accuracy
Benign	0.967	0.970	0.924	0.944	0.966
Malignant	0.968	0.970	0.988	0.977	0.967

The following is a comparison table (Table 8) of the proposed models for breast cancer classification (from our results) versus commonly employed methods of machine learning and some deep learning related to recent literature. The table focuses on some key metrics such as accuracy, specificity, precision and sensitivity, using some results from our models and published work studies for context

Table 8: Comparison of the proposed method with the others

Method / Model	Accuracy	Sensitivity	Specificity	Precision
CNN (Right Breast) Proposed	0.986	0.968	0.973	0.94
CNN (Left Breast) proposed	0.976	0.959	0.983	0.98
ResNet152V2 (Type A, Norm) proposed	1	1	1	1
Mask R-CNN (Malignant)	0.967	0.968	0.97	0.988
Random Forest (RF) (Kumar, Khatri and Mohammadian, 2023) (Salh and Ali, 2022)	0.972	0.974	0.967	0.969
Support Vector Classifier (SVC) (Kumar, Khatri and Mohammadian, 2023) (Salh and Ali, 2022)	0.973	0.97	0.976	0.973
K-Nearest Neighbors (KNN) (Kumar, Khatri and Mohammadian, 2023) (Salh and Ali, 2022)	0.967	0.963	0.97	0.967
Logistic Regression (LR) (Kumar, Khatri and Mohammadian, 2023) (Salh and Ali, 2022)	0.969	0.965	0.971	0.968
Naive Bayes (NB) (Kumar, Khatri and Mohammadian, 2023) (Salh and Ali, 2022)	0.948	0.943	0.95	0.946

7. CONCLUSIONS

This study first uses a model of deep learning for the survival prediction of breast cancer. The idea was to evaluate the influence of given variables separately on the level of life expectancy. After performing a Kaplan-Meier survival analysis on the relevant factors it was observed that the above-mentioned variables affected the survival of patients with BC in the univariate backup. Breast cancer is classified by its stage and treatment, which are benign and malignant, mastectomy and wide local excision. Thereafter, a Cox proportional hazards regression was performed to study a number of factors in relation to survival, WITH the treatment modality. More of the patients that had radiation survived than those who did not have chemotherapy; $\chi = 0.26$ $p = 0.001$. This implies that the treatment received by the patients was influenced by the vary phases.

The research technique has three steps, as previously elucidated. The initial phase employs ResNet152V2 to distinguish between normal and atypical breast cancer, reaching a 98% accuracy rate. The second phase involves the utilization of the Mask R-CNN to differentiate between malignant and benign breast cancer, resulting in a 98% accuracy rate. In another work, the Mask R-CNN is utilized to ascertain the dimensions of the tumor.

Based on the assessment conducted by two radiologists, they fully endorse the model's superiority compared to alternative approaches.

This algorithm exhibits the capacity for additional enhancement, allowing a more sophisticated approach to identifying and eradicating cancer cells inside the identified region. Technological innovations have the potential to boost the capacities of future developments. Furthermore, this approach can also be utilized for other forms of cancer, such as lung cancer.

References

Ackermann, M., Iren, D., Wesselmecking, S., Shetty, D. & Krupp, U. 2022. Automated segmentation of martensite-austenite islands in bainitic steel. *Materials Characterization,* 191**,** 112091.

Alikhassi, A., Gourabi, H. E. & Baikpour, M. 2018. Comparison of inter-and intra-observer variability of breast density assessments using the fourth and fifth editions of Breast Imaging Reporting and Data System. *European journal of radiology open,* 5**,** 67-72.

Altini, N., Brunetti, A., Puro, E., Taccogna, M. G., Saponaro, C., Zito, F. A., De Summa, S. & Bevilacqua, V. 2022. Ndg-cam: Nuclei detection in histopathology images with semantic segmentation networks and grad-cam. *Bioengineering,* 9**,** 475.

Avcı, H. & Karakaya, J. 2023. A novel medical image enhancement algorithm for breast cancer detection on mammography images using machine learning. *Diagnostics,* 13**,** 348.

Cai, H., Huang, Q., Rong, W., Song, Y., Li, J., Wang, J., Chen, J. & Li, L. 2019. Breast microcalcification diagnosis using deep convolutional neural network from digital mammograms. *Computational and mathematical methods in medicine,* 2019**,** 2717454.

Cai, L., Long, T., Dai, Y. & Huang, Y. 2020. Mask R-CNN-based detection and segmentation for pulmonary nodule 3D visualization diagnosis. *Ieee Access,* 8**,** 44400-44409.

Chen, L., Li, S., Bai, Q., Yang, J., Jiang, S. & Miao, Y. 2021. Review of image classification algorithms based on convolutional neural networks. *Remote Sensing,* 13**,** 4712.

Chiao, J.-Y., Chen, K.-Y., Liao, K. Y.-K., Hsieh, P.-H., Zhang, G. & Huang, T.-C. 2019. Detection and classification the breast tumors using mask R-CNN on sonograms. *Medicine,* 98**,** e15200.

Di Micco, R., O'connell, R., Barry, P., Roche, N., Macneill, F. & Rusby, J. 2017. Standard wide local excision or bilateral reduction mammoplasty in large-breasted women with small tumours: surgical and patient-reported outcomes. *European Journal of Surgical Oncology (EJSO),* 43**,** 636-641.

Gouveia, P. F., Oliveira, H. P., Monteiro, J. P., Teixeira, J. F., Silva, N. L., Pinto, D., Mavioso, C., Anacleto, J., Martinho, M. & Duarte, I. 2022. 3D breast volume estimation. *European Surgical Research,* 63**,** 3-8.

Ivanovska, T., Jentschke, T. G., Daboul, A., Hegenscheid, K., Völzke, H. & Wörgötter, F. 2019. A deep learning framework for efficient analysis of breast volume and fibroglandular tissue using MR data with strong artifacts. *International journal of computer assisted radiology and surgery,* 14**,** 1627-1633.

Kim, C.-M., Park, R. C. & Hong, E. J. 2020. Breast mass classification using eLFA algorithm based on CRNN deep learning model. *IEEE Access,* 8**,** 197312-197323.

Kumaraswamy, E., Kumar, S. & Sharma, M. 2023. An invasive ductal carcinomas breast cancer grade classification using an ensemble of convolutional neural networks. *Diagnostics,* 13**,** 1977.

Lin, R.-H., Kujabi, B. K., Chuang, C.-L., Lin, C.-S. & Chiu, C.-J. 2022. Application of deep learning to construct breast cancer diagnosis model. *Applied Sciences,* 12**,** 1957.

Lopez-Almazan, H., Pérez-Benito, F. J., Larroza, A., Perez-Cortes, J.-C., Pollan, M., Perez-Gomez, B., Trejo, D. S., Casals, M. & Llobet, R. 2022. A deep learning framework to classify breast density with noisy labels regularization. *Computer Methods and Programs in Biomedicine,* 221**,** 106885.

Michael, E., Ma, H., Li, H., Kulwa, F. & Li, J. 2021. Breast cancer segmentation methods: current status and future potentials. *BioMed research international,* 2021**,** 9962109.

Militello, C., Rundo, L., Dimarco, M., Orlando, A., Conti, V., Woitek, R., D'angelo, I., Bartolotta, T. V. & Russo, G. 2022. Semi-automated and interactive segmentation of contrast-enhancing masses on breast DCE-MRI using spatial fuzzy clustering. *Biomedical Signal Processing and Control,* 71**,** 103113.

Nasser, M. & Yusof, U. K. 2023. Deep learning based methods for breast cancer diagnosis: a systematic review and future direction. *Diagnostics,* 13**,** 161.

Nayak, D. R., Padhy, N., Mallick, P. K., Zymbler, M. & Kumar, S. 2022. Brain tumor classification using dense efficient-net. *Axioms,* 11**,** 34.

Qi, X., Zhang, L., Chen, Y., Pi, Y., Chen, Y., Lv, Q. & Yi, Z. 2019. Automated diagnosis of breast ultrasonography images using deep neural networks. *Medical image analysis,* 52**,** 185-198.

Raza, M. 2016. *Using survival analysis to investigate breast cancer in the Kurdistan region of Iraq.* City, University of London.

Raza, M. S. & Broom, M. 2023. The Use of Survival Analysis Modelling with Incomplete Data with Application to Breast Cancer. *Asian Journal of Probability and Statistics,* 25**,** 45-69.

Ren, T., Lin, S., Huang, P. & Duong, T. Q. 2022. Convolutional neural network of multiparametric MRI accurately detects axillary lymph node metastasis in breast cancer patients with pre neoadjuvant chemotherapy. *Clinical breast cancer,* 22**,** 170-177.

Saber, A., Sakr, M., Abo-Seida, O. M., Keshk, A. & Chen, H. 2021. A novel deep-learning model for automatic detection and classification of breast cancer using the transfer-learning technique. *IEEe Access,* 9**,** 71194-71209.

Salh, C. H. & Ali, A. M. 2023. Unveiling Breast Tumor Characteristics: A ResNet152V2 and Mask R-CNN Based Approach for Type and Size Recognition in Mammograms. *Traitement du Signal,* 40.

Surendhar, S. P. A. & Vasuki, R. 2021. Breast cancer detection using deep belief network by applying feature extraction on various classifiers. *Turkish*

Journal of Computer and Mathematics Education, 12**,** 471-487.

Wang, X., Ahmad, I., Javeed, D., Zaidi, S. A., Alotaibi, F. M., Ghoneim, M. E., Daradkeh, Y. I., Asghar, J. & Eldin, E. T. 2022. Intelligent hybrid deep learning model for breast cancer detection. *Electronics,* 11**,** 2767.

Whitney, H. M., Li, H., Ji, Y., Liu, P. & Giger, M. L. 2019. Comparison of breast MRI tumor classification using human-engineered radiomics, transfer learning from deep convolutional neural networks, and fusion methods. *Proceedings of the IEEE,* 108**,** 163-177.

Yassin, N. I., Omran, S., El Houby, E. M. & Allam, H. 2018. Machine learning techniques for breast cancer computer aided diagnosis using different image modalities: A systematic review. *Computer methods and programs in biomedicine,* 156**,** 25-45.

Zhang, Y., Liu, Y.-L., Nie, K., Zhou, J., Chen, Z., Chen, J.-H., Wang, X., Kim, B., Parajuli, R. & Mehta, R. S. 2023. Deep learning-based automatic diagnosis of breast cancer on MRI using mask R-CNN for detection followed by ResNet50 for classification. *Academic radiology,* 30**,** S161-S171.

Ahmad, S. & Mouiad, A. (2021) 'Comparative study: 2D object detection & inferencing using Detectron2', Abstract, August, pp. 0–5.

Kumar, M., Khatri, S. & Mohammadian, M. (2023) 'Breast cancer classification approaches-a comparative analysis', Journal of Information Systems and Telecommunication (JIST), 41(1), pp. 2322–1437.

Pham, V., Pham, C. & Dang, T. (2020) 'Road damage detection and classification with Detectron2 and faster R-CNN', Proceedings of the 2020 IEEE International Conference on Big Data (Big Data 2020), pp. 5592–5601. Available at: https://doi.org/10.1109/BigData50022.2020.9378027

Salh, C.H. & Ali, A.M. (2022) 'Comprehensive study for breast cancer using deep learning and traditional machine learning', Zanco Journal of Pure and Applied Sciences, 34(2).

Tahir, K.F., Ali, A.M. & Hadi, G.M. (2024) 'MASK-RCNN on the diagnoses of lung cancer in Kurdistan Region of Iraq', Zanco Journal of Pure and Applied Sciences, 36(1).